MULTI-OBJECTIVE OPTIMIZATION APPROACH TO SOFTWARE PACKAGING USING SEQUENCE DIAGRAMS

BY

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Dedicated to my mother

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

UC	:	Use case
SD	:	Sequence Diagram
OA	:	Optimization algorithm
GA	:	Genetic algorithm
DE	:	Differential evolution
CMA-ES	:	Covariance matrix adaptation-evolution strategy
PSO	:	Particle swarm optimization
ACO	:	Ant colony optimization
BCO	:	Bee colony optimization
QoS	:	Quality of service
ASM	:	Architectural Stability Metric
ExASM	:	Extended Architectural Stability Metric
CEAM	:	Coupling Efferent-Afferent Metric

ABSTRACT

Full Name : [Aliyu Bagudu

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Modularity is an essential attribute of software products/systems. The importance of modularity becomes significant as the size of software system increases. In software architecture, deployment analysis produces partitioning of components in a configuration that optimizes multiple quality of services. At this level, modularity is referred to as packaging. Packaging can be seen as the process of partitioning of classes in a system into a given number of packages to form a packaging configuration. Packaging helps to organize software systems in a manner that enhances maintenance (through enhancement of flexibility) with low cost. These acquired qualities of flexibility and low-cost, make good packaging an essential activity for accommodating ever-changing requirements in software systems. Traditionally, software packaging is done manually by designers based on their intuition and experience. However, as the size of software systems grow, automation of the process becomes essential. There have been several attempts at automatic partitioning of classes into packages. However, most of these attempts emphasize packaging of classes for software development purposes. That is their focus were on how classes are organized/modularized into files, directories and namespaces for developmental purposes rather than for deployment purposes. In recent works, researchers approached solving packaging problem by formulating it as a multi-objective optimization problem. This thesis, proposes an extension to an earlier metric through its interpretation as a Convolutional Neural Network. We have also investigated how different optimization techniques taken from the literature perform in fine-tuning of the metric. Software architectural stability metrics (ASM, ExASM, and CEAM) were implemented and correlations between them and software packaging metric were computed.

ملخص الرسالة

الاسم الكامل:

عنوان الرسالة: نهج متعدد الأغراض الأمثل لبرامج التعبئة والتغليف باستخدام تسلسل الرسوم البيانية

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النمطية هي سمة أساسية من منتجات / أنظمة البرمجيات .أهمية النمطية تصبح كبيرة مع زيادة حجم نظام البرمجيات . وفي هندسة البرمجيات، ينتج تحليل النشر تقسيم المكونات في تكوين يحسن من جودة الخدمات المتعددة .في هذا المستوى، ويشار إلى نمطية كما التعبئة والتغليف .ويمكن اعتبار التعبئة والتغليف عملية تقسيم الطبقات في نظام إلى عدد معين من الحزم لتشكيل تكوين التعبئة والتغليف .التعبئة والتغليف يساعد على تنظيم أنظمة البرمجيات بطريقة تعزز الصيانة) من خلال تعزيز المرونة (مع انخفاض التكلفة .هذه الصفات المكتسبة من المرونة ومنخفضة التكلفة، وجعل التعبئة والتغليف جيدة نشاطا أساسيا لتلبية الاحتياجات المتغيرة باستمرار في أنظمة البرمجيات .تقليديا، يتم التغليف يدويا من قبل المصممين على أساس الحدس والخبرة .ومع ذلك، مع حجم نظم البرمجيات تنمو، أتمتة العملية يصبح أساسيا .كانت هناك عدة محاولات لتقسيم تلقائي للفصول إلى حزم .ومع ذلك، فإن معظم هذه المحاولات تؤكد التعبئة والتغليف للفئات لأغراض تطوير البرمجيات .وهذا هو تركيزهم على كيفية تنظيم الطبقات / نمطية في الملفات والدلائل ومساحات الأسماء لأغراض التنمية بدلا من لأغراض النشر .في أعمال حديثة، اقترب الباحثون من حل لمشكلة التعبئة والتغليف من خلال صياغته كمشكلة الأمثل متعددة الأهداف .هذه الأطروحة، تقترح تمديدا إلى مقياس سابق من خلال تفسيره باعتباره شبكة العصبية التلافيفية .لقد قمنا أيضا بالتحقيق في كيفية أداء تقنيات التحسين المختلفة المأخوذة من الأدبيات في صقل المقياس .وقد تم أيضا صياغة مقياس استقرار معماري جديد للبرامج) إكسسم(، وتم إجراء محاولة لاستخدامه للتحقق من صحة مقياس التعبئة البرمج

CHAPTER 1

INTRODUCTION

1.1 Motivation

Software packaging is the process of partitioning or clustering of all class modules in a software system into a set of clusters/packages for developmental or deployment purposes. In software architecture, a package can be viewed as a component. Components are independent executable units that interact with each other. Components are composition of classes and/or other components [44]. This type of packaging process is referred to as deployment analysis in software architecture.

A packaging configuration is an instance of the set of all possible outputs the packaging process can produce. The term packaging also refers to a packaging configuration. Here we assume that packages in a configuration are nonintersecting sets of classes. This implies that a configuration cannot have more than one instance of a class and equivalently a class cannot be present in more than a single package. Thus the highest number of packages we can have in a packaging is equal to the number of classes in the entire system. That is each class being treated as a package. While on the other extreme case we may have a single package with all the classes.

Packaging for software development purposes has its own benefits such as maintainability, and reusability. Moreover, what is important and of interest to software architecture is the

deployment architecture [44]. The deployment architecture is an arrangement of components of the system in a certain manner for deployment purposes. This has a significant impact on the quality of service (QoS) of the system. The QoS here does not only pertain to the development but most importantly to the use of the system.

In large commercial software systems, composed of many components providing different services, it is desired that the classes are packaged into components based on the services they provide and the intercommunication between them. A general aim is to increase cohesion among classes in the same package and to reduce coupling between packages. Having class modules that provide a single service composed in a single package is intuitive because it will be more efficient in terms of user-interaction response and minimization of latency. Additionally, when a service fails other parts of the system will still function providing services. Maintenance of the system can also be performed on a module without having much impact on the entire system. Based on this intuition, we can decide class modules that should be together in the same package.

However, how to select which class modules to put together may not be straightforward especially in the case of large systems. A single class may be communicating with multiple other classes that are involved in different services or scenarios. That is a single class may be involved in more than a single scenario. Therefore, if decision is made to group packages by services/scenario they partake in, a manual packaging will be almost impossible if the system is too large

Hence, a more systematic approach that can automatically suggest good packaging configurations is essential. In software packaging, there are several competing goals we

want to achieve. If minimizing coupling and maximization of cohesion are our only objectives, we may decide to put all class modules in a single package. However, if we are considering just modularity, we will seek to package the classes in a manner whereby class modules participating in a single scenario and that scenario only, are placed together in a package. However, we want to achieve multiple quality objectives that are conflicting at the same time.

Two major challenges facing effective packaging are: lack of effective metric to quantify the packaging objectives; and large search space to search through for the optimal packaging combination. The latter is termed as combinatory optimization problem [20].

This multi-objective goal coupled with the large search space in which to search for optimal packaging solution, justifies employment of randomized and evolutionary optimization algorithms. Generally, modularity helps in managing complexity; it encourages simultaneous development of different modules; and it better copes with uncertainties [1].

1.2 Problem Statement

Software packaging problem is a hard problem to solve [20][4].

To tackle the difficulty associated with the definition and quantification of quality of a software packaging, metrics have been proposed and hypothesized. The literature review section discusses earlier works.

However, the research gap here is that these proposed metrics need further validation. This problem of further validation applies to many proposed software metrics. That is why these works [23][57][34] are all about further validation of software metrics – either through correlation check with some other more reliable metrics or by other means.

Moreover, a further new techniques for formulation of software packaging quality metrics can also be investigated.

The goals of this thesis are denoted as follows:

Goal 1: Extension of an earlier metric.

Investigation and reproduction of the earlier metric by Ebad and Ahmed [20] and to extent its functionality.

Goal 2: Investigation of the effectiveness of optimization techniques.

The second goal of this thesis is to investigate whether other optimization techniques from the literature will perform better in this optimization problem.

Some of the potential optimization algorithms to investigate are Differential Evolution (DE) [58], Ant Colony (AC) [15], Particle Swarm (PS) [29], Genetic Algorithm (GA) [47], and Covariance Matrix Adaptation- Evolution Strategy (Cma-es) [11].

Goal 3: Investigation correlation between packaging metric and stability metric

To check if there is correlation between software packaging metric and software stability metric. This is to enable us make an intuitive sense of a correlation between software packaging quality and software stability.

1.3 Research Hypotheses

The research hypotheses are denoted as follows:

- Hypothesis 1: The metric used by Ebad and Ahmed [20] can be reinterpreted and extended to make a better software packaging metric.

- Hypothesis 2: Other optimization techniques will perform better than those employed earlier by [20].
- Hypothesis 3: There is a correlation between the software packaging metric and the stability metric.

1.4 Thesis Approach

Convolutional Neural network approach was used to interpret the earlier metric and that provided a way to extend it.

Experiment was conducted to compare optimization algorithms. Meta-heuristic optimization algorithms approach were used. Five trial runs of given combination of selected parameters of the algorithms were recorded. The average of the best score of each trial runs was computed and used to compare the algorithms.

Architectural stability metrics (ASM, ExASM, CEAM) were implemented and were used to check if there exists a correlation between the packaging metric and stability metric. Nine cases of changes to the hypothetical case study were considered. Further four different scenarios of changes to the case study were considered.

Empirical approach was employed in all studies. Real and hypothetical case studies were employed in the empirical studies.

1.5 Thesis Contributions

This thesis offers the following main contributions:

Contribution 1:

An interpretation of the metric as convolutional neural network was developed. It was shown how the metric can be extended through that interpretation. This paves way for investigating how many other software metrics can be interpreted and extended through neural network.

Contribution 2:

Several stability metrics (ASM, ExASM and CEAM) were implemented and there correlation with software packaging metric was investigated. A correlation between software packaging metric and CEAM metric was confirmed through the experimental case studies.

Contribution 3:

Steps to be taken to identifying, analyzing, formulating and solving an optimization (multi or single objective) problem were outlined. This will serve as a guide for researcher pursuing this endeavor.

I have shown clearly the relationship between machine learning and optimization. Helping new and novice researchers understand what they mean and how they relate.

Therefore, others trying to solve any optimization problem will gain some useful insight from this work.

1.6 Thesis Outline

The remaining parts of the thesis are divided into five chapters:

Chapter 2 gives background about multi-objective optimization problem and how they are solved. Learning and validation process was also explained. Meta-heuristic optimization

algorithms approach was described. **Chapter 2** also reviews and discusses earlier work that has been done on software packaging metric. Methodology adopted to solving the different problems related to the research objectives are discussed in **chapter 3**. Results of the investigations are reported and analyzed in **chapter 4**. Conclusions were made in **chapter 5** based on the results.

CHAPTER 2

BACKGROUND

2.1 Multi-objective optimization

In computer science, problems can be classified either as decision or optimization problem [4][45]. Decision problems are the ones with yes or no output solution when given an input instance [64]. Optimization problems involve outputting a solution that either minimizes or maximizes a quantity when given an instance of a problem[45]. All optimization problems have corresponding decision problem component that has to be solved severally in the course of solving the optimization problem [52].

However for the purpose of classifying problems based on asymptotic run time complexity, only decision problems are considered because an optimization problem falls in same complexity class as their corresponding decision problem [12]. That is if a decision problem that is a component of an optimization problem is in given class, then the optimization problem also fall into the same class [12][4].

In classification of problems based on their asymptotic run time complexity, a problem is considered to be in class P if there exist a deterministic algorithm to solve the problem in polynomial run time [4]. A problem is considered to be in class NP, if there exist a nondeterministic algorithm to solve the problem in polynomial run time complexity [4]. There are also other classes such as NP-Hard and NP-Complete [4].

The NP problems (excluding P class) are deemed to be more difficult to solve and have no polynomial time deterministic algorithm to solve them [4]. Moreover most of the practical problems in real life fall in this category [14]. The packaging problem in this work also falls in this category [20].

Optimization problems can be seen as a search problem involving a search for a solution that optimizes an objective value or multiple objective values [52]. The solution can be of one or more dimension depending on the number of variables it has. The number and type of variables - the number and type of values of variables - determine the scope of the search or solution space [52]. A solution is normally referred to as a point, candidate, or an individual. It can be a point or set of points [40].

2.1.1 Solution space

To understand how optimization problems are solved, one needs to understand the idea of solution space. The space where all the solutions of the problems are based. The way a solution to the problem is found is also dependent on the nature of the solution space. This can be seen as a space of a given number of dimensions as the number of variables. There are usually additional predicates that further restricts the points in the solution space. This predicates can be in the form of constraints or bounds. The nature of the space is dependent on the types of variables that make up the space [52]. This space can be imagined as are Cartesian coordinate.

A constraint is a predicate that comprises of a function of the points of the space whose output is related to a value or set of values by an equality relation. Bound predicates are same as constraints predicates however they have inequality relation instead. Both types of

predicates further constrains the points of the solution space to a limited set of points. The term constraint is simply used to refer to both types of predicates [9].

Worth noting is that the variable type of the objective function is distinguishable from variable types of dimension of points in the solution space.

2.1.2 Variable types

- quantitative (orderable):
  - continuous: (differentiable or non-differentiable)
  - discrete: integer
- qualitative: (categorical)

Quantitative variable are those which have ordering among all of its possible values [24]. They are those variable types for which it is valid to compare a pair of it values by an inequality relation. That is it can be said that a value is less, equal, or greater than another.

Variable types of the objective function has to be orderable to be an optimization problem involving minimization or maximization. When the objective function output variables are not orderable, then the problem becomes mixed variable programming (MVP) [31][10][37] that involves searching for a pattern from the solution space. There can be continuous objective function output only if all the variables of the points are continuous [59].

Continuous variable is one whose values span the space of real numbers [33]. They give rise to a differentiable or non-differentiable functions. Differentiability of function matters in the realms optimization because some optimization techniques make use of it to compute the direction of slope [32]. Also for derivative based techniques to be used the objective

function has to be a white-box function whose derivative is computable [32]. In this packaging optimization, the objective is treated as black-box function [20].

Discrete and categorical variables are similar however categorical variable are not orderable while discrete variables are. Caution must be taken when dealing with categorical variable that have discrete labeling because often numbers are used to label articles without necessarily implying any order. The type optimization that deals with only discrete candidate solution is what is called integer programming [49]. While those that involves categorical variables are called combinatorial optimization [50]. Thus, the packaging problem we have is a combinatorial optimization problem [20].

2.1.3 Local and global optimum

Local optimum is a point that has the best value among its immediate neighbors in all directions. Global optimum is the best point among all the local optimums. Most of the optimization algorithms use slope testing techniques to converge to the optimum solution point(s). However, all optimums either local or global have same slope behavior and so there is no way to distinguish the global optimum from other optimum points. Thus, the presence of many local optima, is what actually makes optimization difficult to sovle [63].

Fig. 1 and Fig. 2 illustrates the idea of local and global optima. Fig. 1 has solution space in 1 dimension along the horizontal axis and the objective functionoutput indicated along the vertical axis. Fig. 1 is a minimization problem. Fig. 2 has solution space in 2 dimensions along X and Y axis, and the objective function output indicated along the Z axis. Fig. 2 is a maximization problem.

Fig. 1: Local and global optima (minimization) in 2 dimension

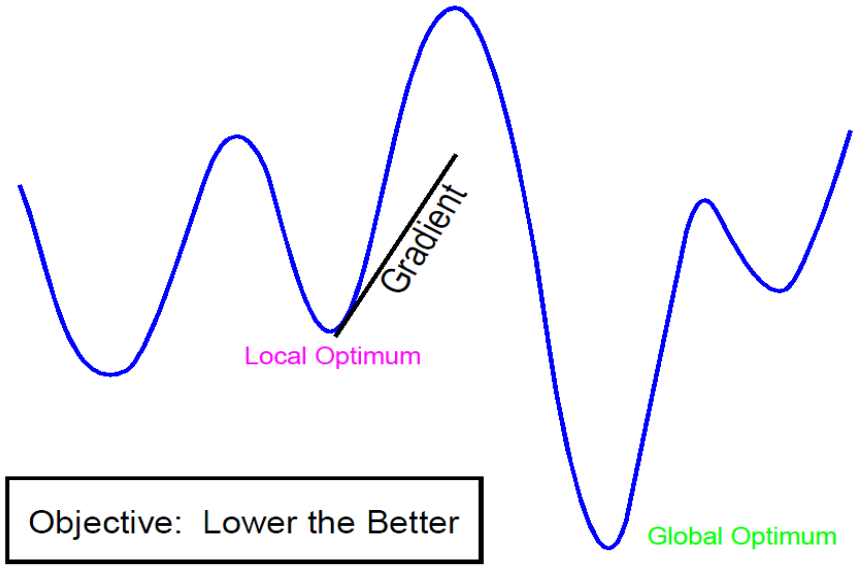
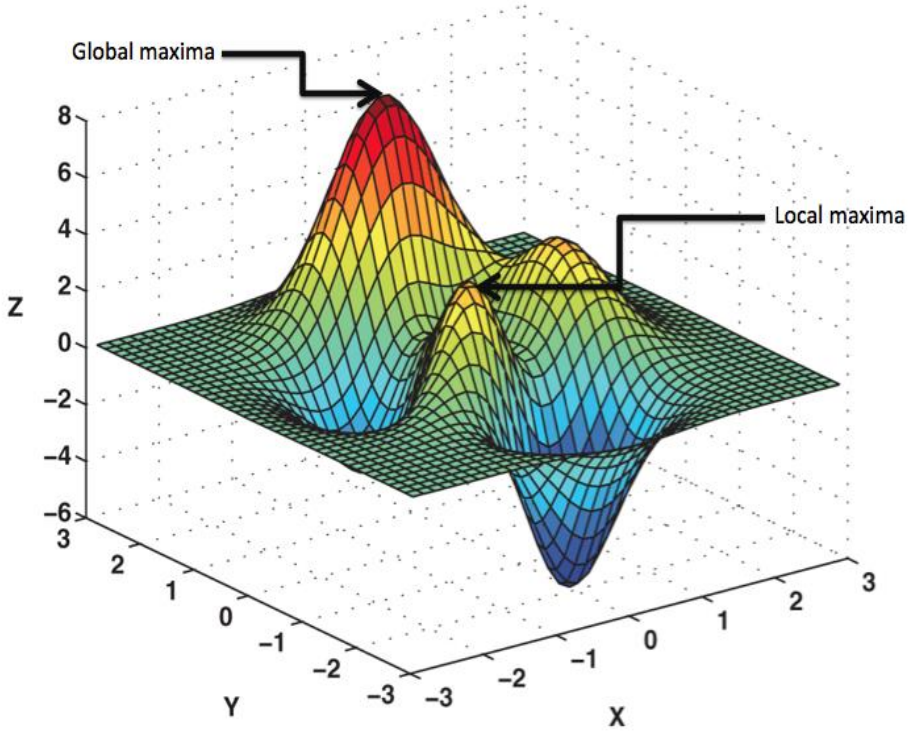


Fig. 2: Local and global optima (maximization) in 3 dimension



2.1.4 Coping with problem hardness

As discussed earlier, there are problems that are hard to solve and have an exponential run time when solved with deterministic algorithms. To cope with those problems, are there techniques used to produce an optimal or near optimal solution that may be appreciable. The solution produced by these techniques may be guaranteed to be within a difference bound of the optimal, or a ratio bound of it [4]. Moreover we may be also able to talk about the properties of the produced solution such as probability of producing the correct answer and the expected run time [4].

Backtracking technique is employed to design an algorithm to solve hard problems when it is desired to obtain an optimal solution from the algorithm. So what this technique does is to use systematic techniques for searching with the hope of cutting down the search space [4].

Approximation algorithms use intuitive heuristics to produce an approximate optimal solution or if lucky the optimal solution to the problem. Randomized algorithm introduce random input(s) in order to guess solutions and thus reduce runtime of producing the solution [4].

Meta-heuristic algorithms are more of general optimization algorithms that are not problem specific. They employ both random input(s) and generic heuristics to solve problems [30]. They are those employed in and one of the focus of this research work. Meta-heuristics algorithms mostly draw their inspiration from the nature [28]. Mimicking how nature solves hard problems. A class of meta-heuristic algorithms is evolutionary optimization algorithms [56][40] (population based) that uses mechanisms inspired by biological

evolution, such as selection, reproduction, mutation, and crossover among population of candidate solutions [48]. They use a population of candidate solutions rather than just iterating over one point in the search space. On the other hand are single candidate meta-heuristic optimization algorithms that evolves through iteration over a single candidate. These single candidates are also normally inspired by natural process such as simulated annealing [61] based on the principle of cooling of molten metal.

2.1.5 Single and Multiple objective functions

In optimization problem there can be more than a single objective function [65]. These objectives may even be conflicting with each in the sense that changing the value of a variable of a solution point may lead to an increase and the other decreasing [6]. However contradicting objectives are not actually the main problem because any of the objectives can easily be negated to make them all have a single objective (either minimization or maximization) [17].

There are different approaches for solving multi-objective optimization problems (Aggregating, Population-based non-Pareto, Pareto-based non-elitist, Pareto-based elitist approaches) [6] . The scope of this work is Weighted sum Aggregating approaches [6].

The problem however, is how should these objectives be combined to form a single global objective function in an aggregating approach manner? The truth is we do not actually know exactly how to until we have some more information about the relation between the objective functions. This relationship implies how the objectives are combined to formulate the global objective function. To find the global optimum one has to find all the local optimums and then compare them.

An objective function is a function of input variables of the solution space the same way the global objective function is a function of each objective functions that combine to form it. Thus, we can look at variables as objective functions in single objective function and in the same way objective functions as variables in multiple objective function.

The simplest combination will be assuming that all objective functions have equal weight and could then be added to formulate the global objective function. This simple idea can be further extended by further assuming that the objective functions have different weights that signifies what percentage they contribute to the global objective function. This way, each objective function is multiplied by a respective weight parameter and the products are added to formulate the global objective. Another very important question to keep in mind is how do we know the weight of those parameters [22]? This simple way of formulating the objective function can be termed as a linear regression (linear combination) objective function. Higher polynomial terms and their respective weights can also be added to objective function to form polynomial regression. Thus we can have objective function formulated as logistic function in logistic regression and so on.

- We can consider objectives as variables $x_1, x_2, \ldots, x_n$
- We have several ways of combining multiple objectives into a single one x.
- Make all objective have single direction: either all minimization or all maximization by multiplying by -1 where needed
- It could be as simple as linear combination [6]:
    - $x = x_1 + x_2 + \ldots + x_n = x_v$

- linear(x_v)

- weighted linear combination [6][22]
  - $x = w_0 + w_1*x_1 + w_2*x_2 + \ldots + w_n*x_n = x_v^T w_v$
  - weightedLinear($x_v^T w_v$)

- Or more complex such as:
  - Logistic (linear, normalized) [36]
    - $x = 1/[1 + \exp - (w_0 + w_1*x_1 + w_2*x_2 + \ldots + w_n*x_n)]$
    - logistic($x_v^T w_v$)
  - Radial basis regression(nonlinear) [62]
    - $x = \exp[-(x_v - c_v)/2r^2]$
    - localweight(x_v ,c_v,r^2)
  - Polynomial regression(nonlinear) [25][54]
    - Polynomial interpolation
    - $x = (x_v^T w_v + c)^d$
    - Polynomial(x_v ,w_v , c , d)
  - A neural network (nonlinear, normalized) [53][26]
    - Where each unit is logistic or sigmoid function

Fig. 3: Graph of logistic function

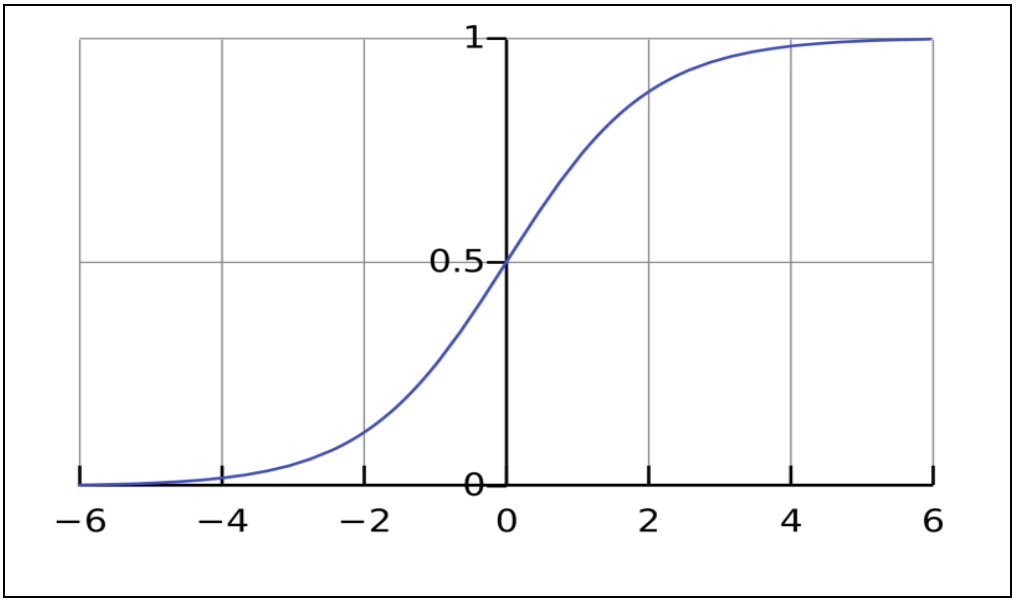
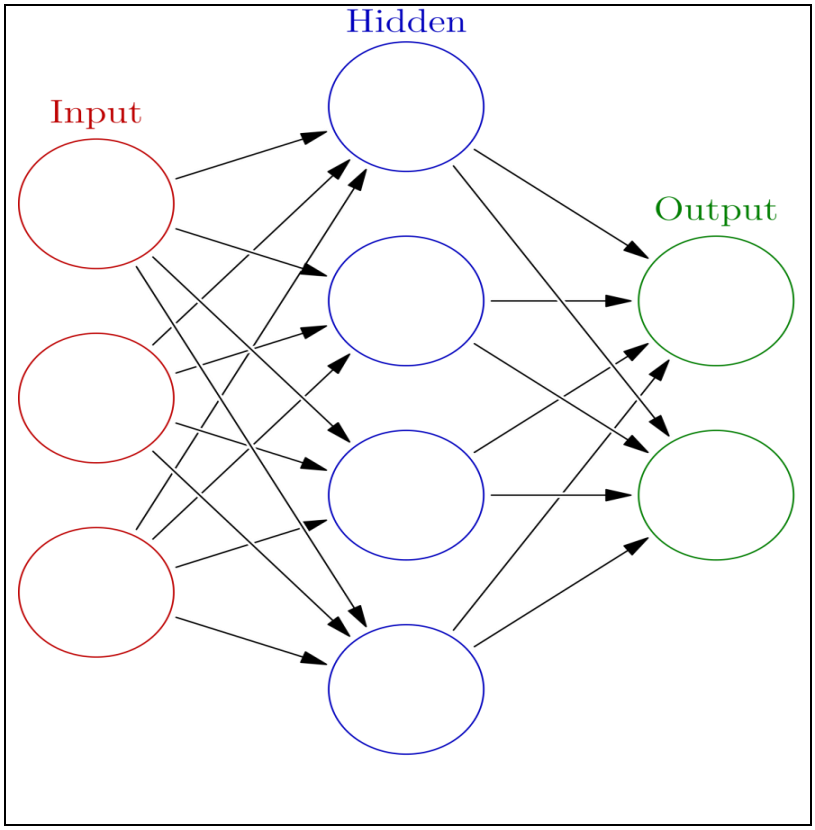


Fig. 4: Graph of Neural Network (NN)



However, we still have those questions that arise such as which type of objective function [6] is suitable or what the value of the parameters [22] should be? The answer is: we don't know and an investigation is necessary. It then becomes a statistical learning problem where we learn what parameters best suits the problem. It can also be called a machine learning problem. However, in a learning process examples are required to be used to learn the best possible value of the parameters. An objective function formulation with all its parameters is called a (statistical) model. This is also called a family of objective functions where for each unique combination of values of the parameters we have a member of the family. The process of learning the values of the parameters is known training the model.

However, in many context, getting a sufficient (significant) number of examples to train a model is challenging because they are difficult to acquire and encode. In this cases assumptions are made.

Moreover, there is principle of Occam's razor that states that among competing hypotheses, the one with the fewest assumptions should be selected. This can be put in another way that the simplest assumption is the best assumption in the absence of evidence or more evidence. That we should not complicate matters beyond necessity. By this principle it is always good to assume a linear combination objective function. Linearity is intuitive and easily assimilated by human reasoning.

2.1.6 Model evaluation and selection

Model evaluation is process of measuring how well a model represent the true system. Generalization error computed using cross-validation technique is used in model evaluation. The process where the model that produces the least generalization error is

selected is called model selection. Model validation is testing to see if selected model's evaluation meet certain criteria such as statistical significance or error threshold. However to perform evaluation in this manner training and testing data are needed to the extent of validation criteria that are required.

In this work however, the validation process used is experts' opinion. The validation is also performed based on hypothetical and real case study. The hypothetical case study is used to learn the parameters (build the model) that produce solutions corresponding with expert opinion. This is synonymous to building a miniature machine model in engineering process to conduct test about a proposed gigantic real machine. This way experiments can be feasibly conducted (though with limitations) which would have been very expensive or near impossible with the real model. So the hypothetical case study serves as the miniature machine model on which experiments are conducted.

2.2 Meta-heuristic optimization algorithms

Meta-heuristic algorithms are more of general optimization algorithms that are not problem specific [30]. They employ both random input(s) and generic heuristics to solve problems. They are those employed in and one of the focus of this research work. Meta-heuristics algorithms mostly draw their inspiration from the nature [63][28]. Mimicking how nature solves hard problems. A class of meta-heuristic algorithms is evolutionary optimization algorithms [35][40] (population based) that uses mechanisms inspired by biological evolution, such as selection, reproduction, mutation, and crossover among population of candidate solutions. They use a population of candidate solutions rather than just iterating over one point in the search space. On the other hand are single candidate meta-heuristic optimization algorithms that evolves through iteration over a single candidate. These single

candidates are also normally inspired by natural process such as simulated annealing [61] based on the principle of cooling of molten metal.

A common aspect of all meta-heuristic algorithms is that they have a heuristic mechanism (operation) of producing new solution(s) from one generation to another. The general term for this mechanism is called tweaking of the point(s) [30]. For example genetic algorithm [48] utilizes 2 different tweaking mechanisms: mutation, and crossover. Other algorithm's tweaking mechanisms can also be viewed as mutation or crossover or utilization of both.

2.2.1 Exploitation and Exploration

The tweaking mechanisms (heuristics) of these algorithms are meant to account for 2 goals: exploitation and exploration [56].

Exploitation consists of probing a limited (but promising) region of the search space with the hope of improving a promising solution S that we already have at hand. This operation amounts then to intensifying (refining) the search in the vicinity of S. By doing so, we would be doing, de facto, a local search.

Exploration, on the other hand, consists of probing a much larger portion of the search space with the hope of finding other promising solutions that are yet to be refined. This operation amounts then to diversifying the search in order to avoid getting trapped in a local optimum. By doing so, we would be doing, by de facto, a global search.

Thus, the parameters of the different algorithms have a role they play in pushing for either of the goals depending on their values.

2.2.2 Genetic algorithm (GA)

Genetic algorithm (GA) is a population based optimization technique. It is inspired by natural evolutionary process theory of selection – survival for the fittest. In this optimization process the fittest members of the population have the highest chance of producing the next generation. A solution is regarded as an individual competing among other individuals in a population. In the natural evolution process, kind of individuals for subsequent generations depends on the natural operations such as crossover, inheritance, mutation and selection [48].

Genetic algorithm can be seen as a framework for many evolutionary optimization algorithms where the heuristics of an algorithm can be made analogous to one of the stages or operations of genetic algorithm. With this view, other algorithms can be integrated into MATLAB GA toolbox to harness the features of the toolbox such as algorithm data collection and visualization.

2.2.3 Covariance matrix adaptation-evolution strategy (CMA-ES)

The CMA-ES (Covariance Matrix Adaptation Evolution Strategy) is an evolutionary algorithm that uses adapted covariance matrix to define a n-sphere around the specified feasible region range [11]. It is used for highly non-linear, non-convex, and black-box optimization problems [11]. CMAE-ES is regarded as a state-of-the-art optimization algorithm because of it use as a standard optimization tool across the industries [11]

2.2.4 Particle swarm optimization (PSO)

As with many other optimization algorithms, particle swarm optimization (PSO) is an optimization algorithm (OA) that mimics biological animal behavior. In particular, PSO mimics optimal behavior of swarm birds (particles) in search of food (solution).

PSO uses simple mathematical formula to calculate and track the position and velocity of each particle [29].

Further details on the working of PSO can be found in [51] where some theoretical convergence conditions were also discussed.

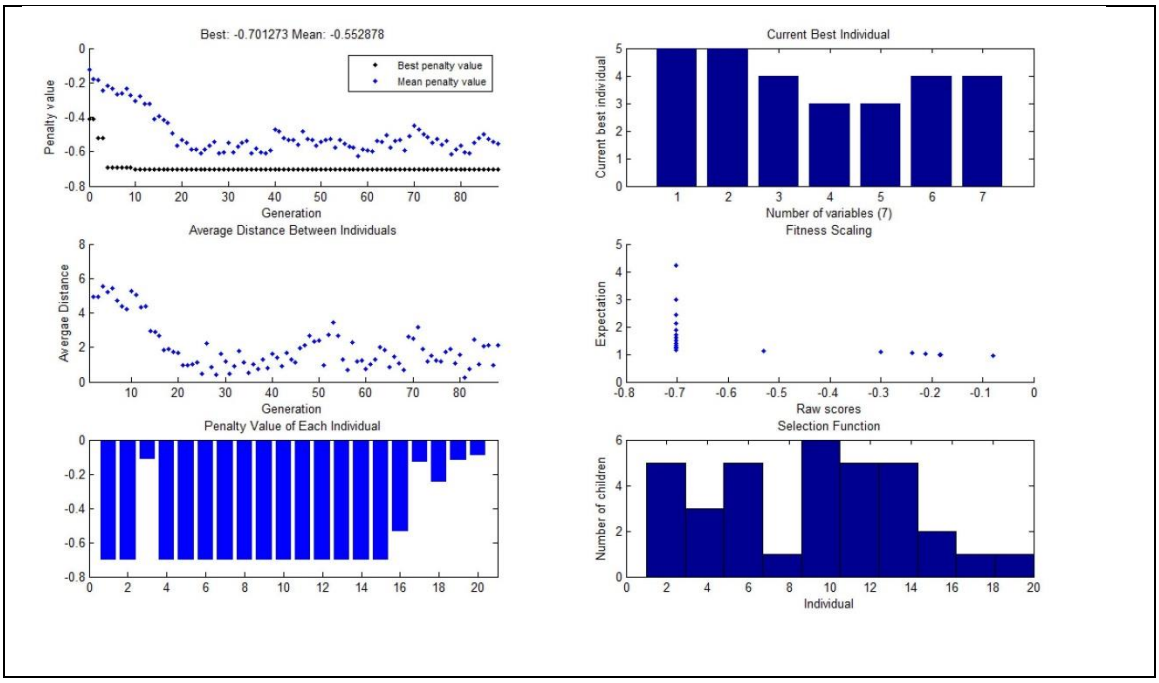
2.2.5 Differential evolution (DE)

An important aspect of global optimization using meta-heuristics is the generation of initial population especially for the population-based heuristic optimization methods. Differential Evolution is a relatively recent population-based search heuristic used by engineers to solve continuous optimization problems. It does not only use simple evolutionary strategy but also functions significantly faster and in robust manner when it comes to solving optimization problems, hence high likelihood to find the global optimum. It has a wide acceptability due to the fact that it has a very few number of parameters and has a compact structure with a small code. Most of the studies have been proposed in order to improve the performance of DE. A number of the studies employ tuning or controlling the parameters of the algorithm and improving the mutation, crossover and selection mechanism [58] [2].

2.2.6 Performance assessment

There several factors that could be used to assess the performance of the algorithms. Some of this factors have an associated graphical plot that could be used to visualize them. The data pertaining to these factors are collected at each generation (iteration). Fig. 5 shows the visualization of some these factors. This visualization depicts GA with 7 dimensional data points, with population size of 20, and made about 90 iterations. Below is a list of factors and their descriptions used to evaluate the algorithms.

Fig. 5: OA performance visualization



- **Best fitness** plots with black dots the best function value against generation and in the blue dots is plot of **average function value** of individuals in a generation versus generation. It is used to monitor whether the algorithm's "best value ever" is only getting better as it makes progress. The average score per generation gives a feel of whether the algorithm's population converges as it progresses and thus giving a feel

of exploitation. Caveat here is we may try to use this to get a feel of exploration at the end if the average fitness value does not equal best fitness value. The average fitness could may best fitness value in case where all optimum solutions discovered have same value. This may even be more likely where multiple solution representations (genotype) could refer to a single solution. In addition different solution points could have same score. We could also get a feel of whether the algorithm is merely a random process throwing random points around in which case the average fitness value will show a constant trend.

- **Best individual** plots the vector entries of the individual with the best fitness function value in each generation. Therefore, what the graph currently shows is the best individual the last generation.

- **Average Distance** plots the average distance between individuals at each generation. This enables us to visualize how wide spread the individuals in the population are. This will enable us know whether the algorithm balances between exploration and exploitation. if for instance the average distance is zero at a given generation, that means all the population members have converge to a solution point. We may want the average distance to show a decreasing trend to give us a sense of convergence and thus exploitation. However, we may not want the average distance to converge to zero in order to guarantee that even at the last generation the solution points are apart to ensure that exploration has taken place.

- **Expectation** plots the expected number of children versus the raw scores at each generation.

- **Scores** plots the scores of the individuals at each generation. This enables us to visualize scores of all individuals to get a sense of diversity among the population which implies exploration. What the graph currently shows are the individual scores at the last generation. If the number of individuals is large then Score **diversity plots** can be used instead to plot a histogram of the scores at each generation.

- **Selection** plots a histogram of the parents. This show the individuals in the current generation and their likelihood of being selected has parents to produce the next generation. What the graph currently shows are the likelihood of individuals at the last generation. This can be useful if we are interested in monitoring exploration to see if the algorithm gives any chances at all for individual with low score.

2.2.7 Parameters types

There are three types of parameters involved in optimization experiments. First, is model parameter - for example the weight of parameters discussed earlier. They are later used in prediction with the model. Second, it is hyper-parameter that helps to choose a model from a complex super-set model. They may also be used in prediction with the model if no effort is made to identify the model selected from the super-set model. Third is algorithm parameter which also helps choose a model but is specific to an algorithm and only used in the optimization process. They don't appear when the model is used for prediction. However, both hyper-parameter and algorithm parameter can be simply referred to as hyper-parameter (or meta-parameter). Moreover, we are dealing only with model and algorithm parameter in our case.

2.2.8 Parameter Search Techniques

Search grid is a manual parameter search technique which discretizes the values of all factors involved in an experiment to specific respective set of values, and evaluate all combinations of factor values so that the best parameters' values combination that produces the best fitness can be identify.

Hyper-parameter optimization is broader term for techniques used in fine tuning of hyper-parameters and algorithm parameters to select an optimization model. The other type of hyper-parameter tuning technique is meta-optimization, where the parameter search problem is also formulated as an optimization problem to obtain value(s) of parameter(s) that correspond to local optima. That is you have an optimization problem inside another which is being used to fine tune its parameters.

2.3 Literature Review

2.3.1 Packaging quality metric

Many approaches have been proposed in the literature that attempt to apply different methods and algorithms in order to achieve design modularization for the components of software systems.

Mancoridis et al. [42] [41] developed a special tool, called Bunch. It uses hill climbing and genetic algorithm for optimizing their clustering objective function. The system is based on the relationship between entities in the source code. The modularization quality (MQ) that is calculated as trade-off between the intra-module and inter-module connectivity, was used as objective function. For representation of the system, they calculated the MQ by subtracting the average inter-connectivity and the average intra-connectivity. They used a

module dependency graph (MDG) that is built based on the components of the system and relationships that exist in the source code.

Liu et al. [35] attempts to solve problem of minimization of traffic across computer network involving multiple servers and users by formulating the multi-objective problem as partition of users into a number of nonintersecting sets equal to the number of severs. The approach tries to optimization such that within-partition dependencies are high and between-partition dependencies are low. They used Grouping Genetic Algorithm (GGA) that is used for large -scale partitioning problem. Their ultimate aim was to minimize network traffic in the entire network.

Bauer and Trifu [8] presented a way to produce a packaging by combining clustering with pattern recognition algorithms to recover subsystems similar to what software engineers achieved by reverse engineering.

Using the Bunch tool, Doval et al. [16] employed GA algorithm to seek an optimal grouping using modularization quality objective function. They used roulette wheel selection while standard mutation and crossover were used. The used crossover rate of 80% for populations of 100 individuals and 100% of a 1000 individuals. The mutation rate used is 0.0004log (N). Where N is the number of nodes in the MDG.

Mitchell and Mancoridis [46] extended the Bunch tool by addressing a shortcoming that makes it produce clusters that minimize the inter-edges exiting in clusters rather than minimizing the total number of inter-edges all together. Thus, they came up with a modification of MQ and integrated it into the tool. The new MQ supports MDGs with edge weights, while the original MQ measurement did not.

Seng et al. [55] used a combination of software metrics and design heuristics to formulate a function to calculate the quality of subsystem decomposition. They also used group genetic algorithm (GGA) as the main algorithm applied in this situation with the fitness function being a multi-objective function that accounts for cohesion, complexity, coupling, cycles, and bottlenecks.

Alkhalid et al. [3] proposed an approach on the package level. They used the refactoring approach, and they classified the classes in two approaches: An approach where number of packages are fixed; and an approach where number of packages is variable. They applied different clustering approaches whose results were compared with those of two software engineering experts/faculty to validate their results. A similarity measure proposed by Lung et al. [38] was used in their packaging approach.

Abdeen et al. [1] proposed an approach to enhance the existing modularization by minimizing the inter-package connectivity. They did several experiments and they described the dependency quality as a weighted average of the common closure quality and acyclic dependency quality. Compared with the previous methods, their approach makes provision for setting constrains such as the size of the package, modularization structure, etc.

Earlier works such as Ebad and Ahmed [20] emphasized packaging of classes for developmental purposes. Their focus was on how classes are organized/modularized into files, directories and namespaces for developmental purposes rather than for deployment purpose. In partitioning of modular systems, partitioning based on functional aspects was emphasized [20]. Moreover, prior to their approach all attempts at automatic packaging

were not function driven. This led Ebad and Ahmed [20] to embark on the course functionality based software packaging. Ebad and Ahmed [20] validated there approach using three means: first is validation against theoretical properties of good metrics; second is an experiment on hypothetical case study; and third is an experiment of on real-case study.

Ebad and Ahmed [20] proposed a metric to separate the classes of class diagrams into packages in the architecture design phase. They presented this method to address modularization. They showed that by allowing each package to offer a single function and that function being completely executed within that package, we can achieve a cohesive modularization. They validated the metric against the theoretical properties and they applied it to two search techniques: exhaustive search approach; and heuristic search approach. They also applied their approach to two case studies whose outcomes were encouraging.

They formulated a multi-objective packaging metric on which they employed three optimization algorithms - Simulated Annealing (SA), GGA-Evolver Genetic Algorithm (GA) and Hill Climbing (HC). However, the shortcoming with their approach is that packaging configuration with all the classes in one package is scored highest by the metric at the expense of desirable feasible configurations that gives realistic number of packages. In this case if the number of solutions the optimization algorithm (i.e. GA) is required to produce is few then realistic solution may even not be present because the GA is supposed to produce the fittest possible individuals it can produce. Moreover, if the optimization algorithm is required to produce too many solutions then, it will consume much time and

manual selection still has to be done on the many solutions produced to choose a realistic solution.

The packaging metric [20] was referenced by Ebad [18] in his work on measuring software requirement volatility. This reference is made as a result of use of same JHotDraw software as case study and the use of use of similar theoretical validation approach. The packaging metric was also referenced in another work by Ebad [21] where they reviewed and evaluated cohesion and coupling metrics at packaging and subsystem level.

2.3.2 Architectural stability metrics

Jazayeri [27] used a retrospective approach to assess software architectural stability where 20 releases of a telecommunication software was used as a case study. A metric was not formulated in this work however 3 analysis approach were employed in the assessment – simple metric analysis, Hidden module coupling, and Color visualization. The simple metrics were all based on size of system and they include number of programs, number of added programs, percentage of added and changed programs, and size of modules. The hidden module coupling simply involves physically examining which programs always change together in each releases to ascertain if the is certain relationship between them. In color visualization, color percentage bars were used to display a history of a release.

Aversano et al. [5] work was based on investigating stability of software projects through software project life cycle with the aim of ascertaining software components that are stable enough to be reused in other projects. They defined Core Design Instability (CDI) and Core Calls Instability (CCI) metrics. The metrics were based on architectural core - which is

regarded as the packages that are involved in 80% of inter-package communications. Where CDI accounted for number of packages, CCI accounted for number of inter-package calls. Both CDI and CCI were defined in the same manner as ASM. To simply put it ASM as same idea as CCI but in ASM all packages are used instead of the so called cores. Real software projects from SourceForge were used as case studies in the work.

In the work done by Bansiya [7], a metric called extent-of-change (EoC) was proposed as a measure of software framework architectural stability. The properties used to calculate EoC are Number of Classes, Number of Hierarchies, Number of Single Inheritances, Number of Multiple Inheritances, Average Depth of Inheritance, Average Width of Inheritance, Number of Services, Number of Parents, and Direct Class Coupling. The main difference between this approach and ASM is that this approach is at class level. This methodology was applied to the Microsoft Foundation Classes (MFC) and Borland Object Windows (OWL) application framework systems to compute the structural characteristics and thus the extent-of-change in several releases of the frameworks. The result shows that the latest versions of both software systems were the most stable.

Ma et al. [39] worked on assessment stability of UML meta-model. This method evaluates six quality attributes such as functionality, effectiveness, understandability, extendibility, reusability, and flexibility from eleven design properties including design size, hierarchies, abstraction, encapsulation, coupling, cohesion, composition, inheritance, polymorphism, messaging, and complexity. Normalized extent-of-change was computed using the eleven properties in similar way as in the work of Bansiya [7]. The method conducts the assessment of stability and design quality to UML meta-models in versions of 1.1, 1.3, 1.4, 1.5, and 2.0.

The work of Tonu et al. [60] they employed both retrospective and predictive approaches to assess architectural stability software systems. In their retrospective approach, source code property measures related to program growth rate (Line of code, number of functions), program change rate (number of changed functions, number of changed function calls), cohesion (percentage of intra-subsystem calls) and coupling (percentage of inter-subsystem calls) were collected and their trends were assessed. In this work the properties were not harmonized into a single metric but were each individually examined. The predictive analysis was then made afterwards to determine evolution-sensitive and evolution-critical parts of the system. The result of the retrospective analysis is used to determine which parts are evolution-sensitive based on high percentage of coupling. From the evolution-sensitive some parts are further deemed evolution critical after analysis is made to determine if the high coupling is logically justifiable. Just as ExASM, this approach considered both intra and inter-subsystem calls. Their proposed approach was applied on two open source spreadsheet software systems, Gnumeric and KSpread.

Robert C Martin in his book, Agile Software Development: principles, patterns, and practices [43], described a package's instability is the percentage of its efferent coupling from total coupling. Where total coupling is described as sum of afferent coupling and efferent coupling. Both afferent and efferent coupling are defined by inter-package connection. In this thesis work, a stability metric (Coupling Efferent-Afferent Metric - CEAM) based on this was implemented and an attempt was made to use it to validate the packaging metric.

A metric by Ebad and Ahmed [19] called Architectural Stability Metric (ASM) quantifies the proportion of change in the inter-package connections between 2 versions of a software

system. ASM is metric purely based on inter-package connections. Afterwards, extension was made to ASM called Extended Architectural Stability Metric (ExASM) that considers both changes intra-package and inter-package connections.

Table 1: Summary of the architetural stability metrics

Author	Level	Artifact	No. of properties	Validation method	Description	Properties
Jazayeri [27] 2002	Architecture	Code	3	Case Study	Evaluates structural stability using retrospective analysis	Size of sys (# of prog, # of added prog, % added and changed, size of modules), Hidden module coupling, Color visualization
Aversano [5] 2013	Architectural	code	6	Real case study	Proposes CDI and CCI metrics to assess architecture stability	CDI, CCI
Bansiya [7] 2000	Class	code	9	Real case study	Introduces a methodology to assess framework architecture stability based on extent of change	Number of Classes, Number of Hierarchies, Number of Single Inheritances, etc.
Ma et al. [39] 2004	-	UML	6	UML models	Uses Bansiya [19] methodology	Design size in meta-classes, Number of hierarchies, etc.
Tonu et al. [60] 2006	Architectural	Code	4	Real case study	Combines retrospective and predictive evaluation	Growth Rate, Change Rate, Cohesion %, and Coupling
Robert C Martin [43] 2000	Architectural	Code	2	-	Bases stability on the ratio of efferent and afferent inter-package connections	Afferent and efferent coupling
Ebad and Ahmed [19] 2015	Architectural	Code	1	Real case study	Measures the percentage of change in inter-package connections after evolution.	Changes in Inter-package connection

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Fitness function for Functionality-based software packaging using sequence diagrams

The main idea in this work is to enable packaging decisions right from architectural design level rather than the source code level, using the sequence diagrams. A sequence diagrams realize a use case.

There are two popular and competing objectives in software design and organization. First is the desire to have loosely (lowly) coupled system parts and second is the desire to have highly cohesive system parts. In this context loose coupling implies that each use case should consider the least number of packages. Loose coupling reflects that the packages are self-contained, and offers a complete function with as little dependency on other packages as possible. While high cohesion implies that the classes in each package are related to each other and that they contribute the same use case.

Thus, this are the two main goals (objectives) considered in the development of the fitness function for software packaging. We call them usecase coverage and class relevancy respectively.

Therefore, the two objective can be combined formulate a single objective called **overallpackaging** of a system. Going by the principle of Occam's razor mentioned earlier, the two objectives can be linearly combined as follows:

Ebad and Ahmed [20] defined the overallPackaging metric as:

$$\textit{OverallPackaging(system)} = \textit{Avg(PackagingQlty(Pi))}$$

where: PackagingQlty(Pi)) is the packaging quality of a package Pi, and is calculated as:

$$\textit{PackagingQlty(Pi)} = Wu \times \textit{degree of UC coverage by Pi} + Wc \times \textit{degree of class relevancy of Pi}$$

where: Wu is the weight of the UC's coverage in a package and Wc is the weight of the class relevancy in a package, so that Wu, Wc ∈ [0, 1] and Wu + Wc = 1.More details about the definition of the metric can be found at [20].

Fig. 6: Neural Network Graph of the metric (1)

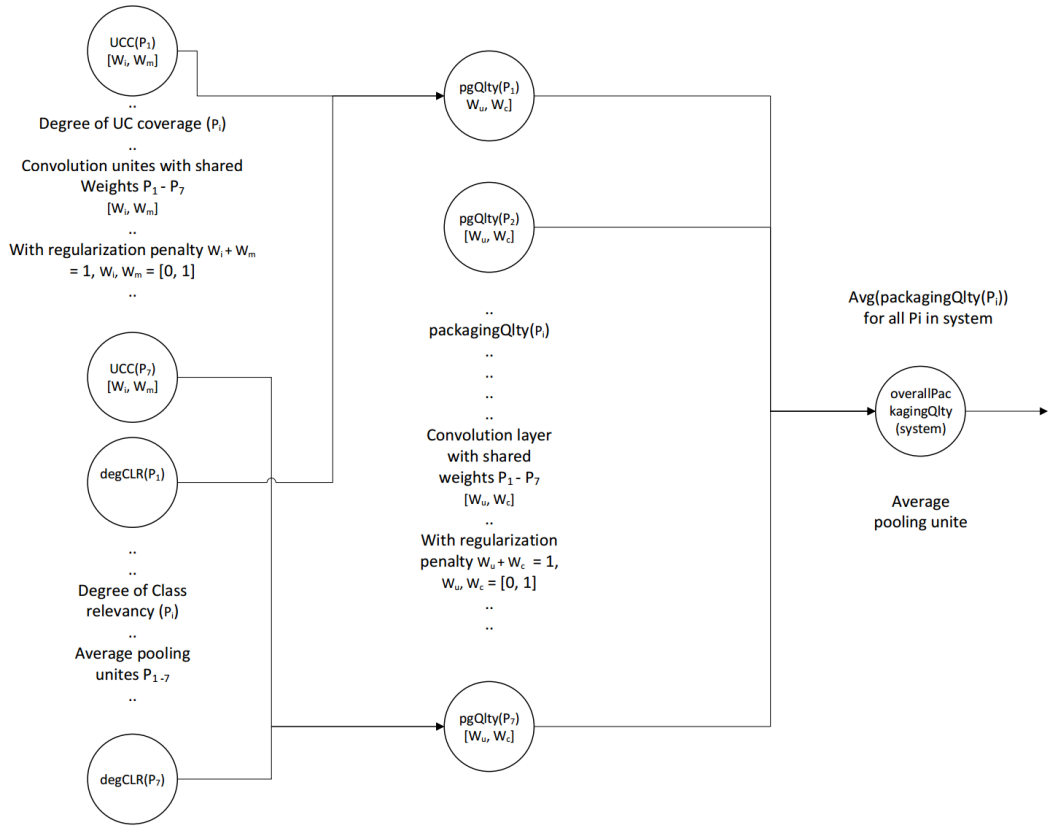


Fig. 6 visually illustrates the packaging metric and shows how it is built hierarchically. It also shows how the metric is interpreted as a convolutional neural network. This is the top most part of the hierarchy where the packaging metric is formulated from lower level features.

Fig. 7: Neural Network Graph of the metric (2)

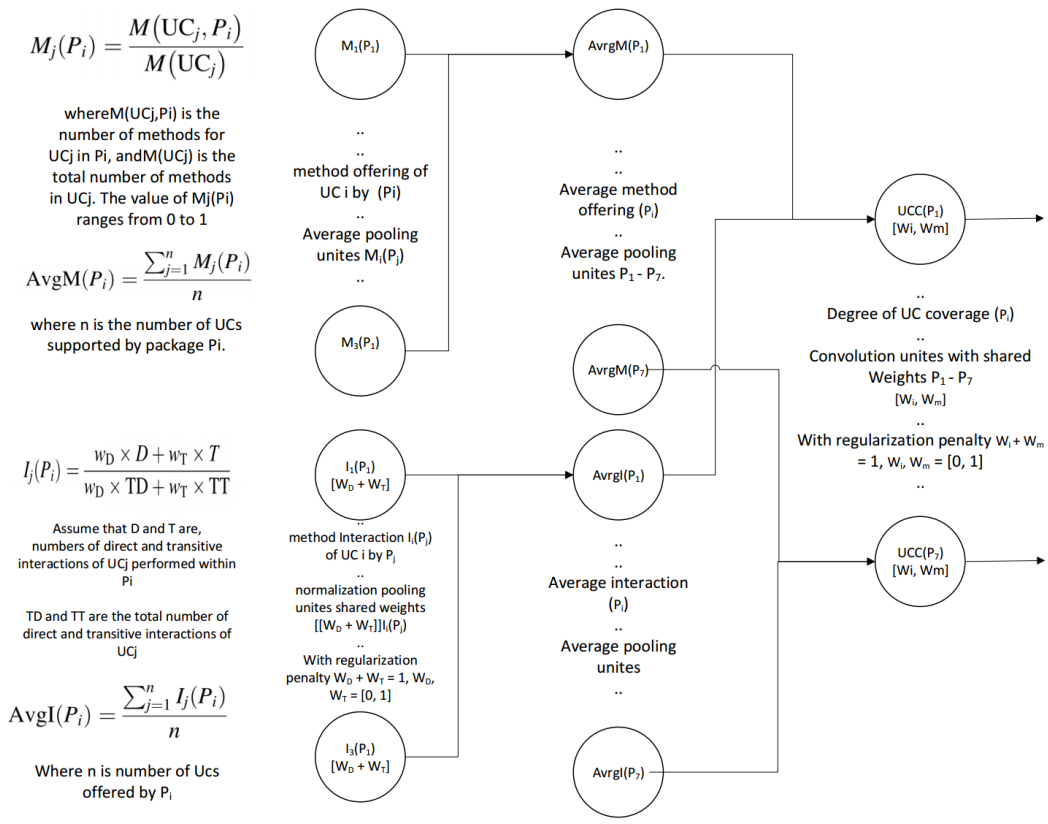


Fig. 7 visually illustrates the packaging metric and shows how it is built hierarchically. It also shows how the metric is interpreted as a convolutional neural network. This is the second level after the top most part of the hierarchy where the packaging metric is formulated from lower level features.

Fig. 8: Neural Network Graph of the metric (3)

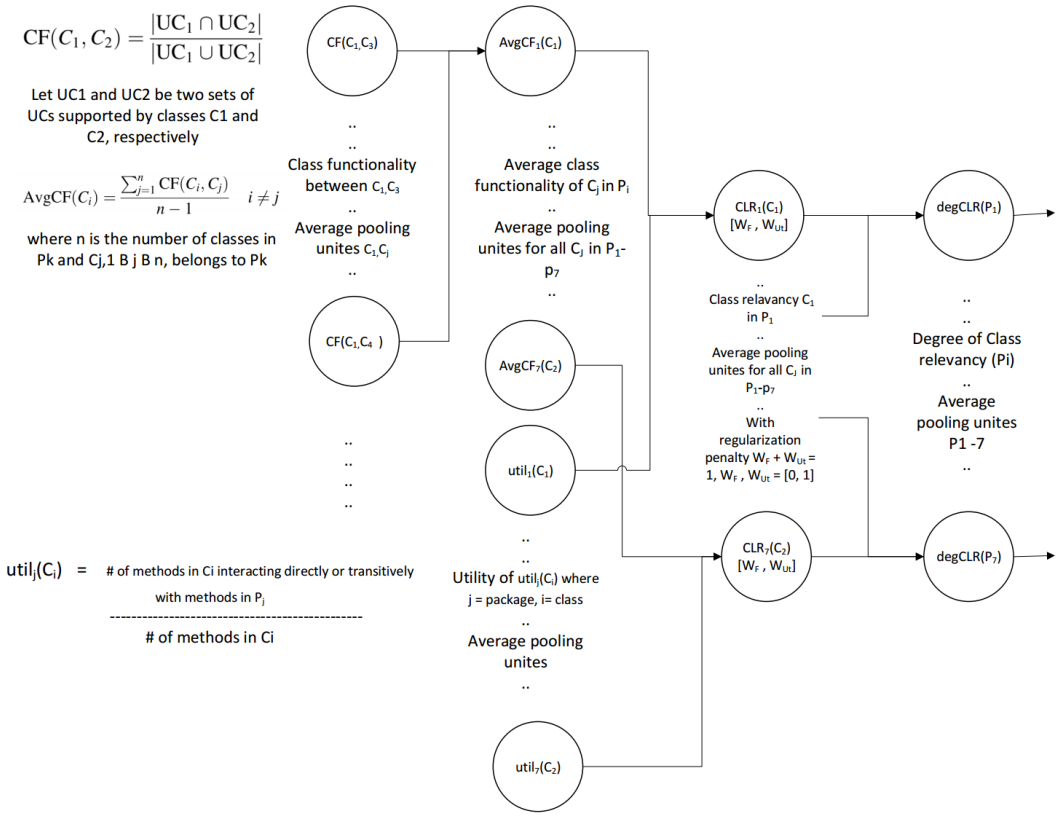


Fig. 8 visually illustrates the packaging metric and shows how it is built hierarchically. It also shows how the metric is interpreted as a convolutional neural network. This shows the last part of the hierarchy where the packaging metric is formulated from lower level features.

3.1.1 Degree of UC coverage

The Degree of UC coverage measures how well a package confines itself to just realization of minimum number of UCs as possible.

Degree of UC coverage by a package P, can be seen as a composition of two lower level factors: (1) the percentage of UC interaction performed within P, and (2) the provision of methods for the UC's SD from within P.

The interaction factor can be further divided into two types, direct and indirect. Direct interaction implies method call involving a method calling another one directly as opposed to through some other methods.

Given usecase UCj from set of UCs of the system and package Pi from set of packages in the packaging configuration of the system. Let D be the number of method calls in the intersection of direct method calls within UCj and Pi. Let T be the number of method calls in the intersection of indirect method calls within UCj and Pi.

Further, let TD be the total number of direct method calls and TT the total number of indirect (transitive) method calls of UCj.

Therefore, to compute the ratio of UCj method calls performed within package Pi, Ij(Pi) is calculated as:

$$\boldsymbol{Ij(Pi)} = \frac{\boldsymbol{wD \times D + wT \times T}}{\boldsymbol{wD \times TD + wT \times TT}} [20]$$

Where wD and wT are weights for the direct and indirect method calls, respectively, and since wD, wT $\in$ [0, 1], wD + wT = 1.

Thus we can compute the entire interaction of package Pi as the average of the interaction measures of all UCs offered by Pi:

$$\boldsymbol{AvgI(Pi)} = \frac{\sum_{j=1}^{n} \boldsymbol{Ij(Pi)}}{\boldsymbol{n}} [20]$$

where n is number of UCs offered by Pi

The second component factor of the UC coverage aspect is the offering of the UC's methods by the package. The method offering for UCj by package Pi, Mj(Pi), is defined as the ratio of the number of methods in the intersection of sets methods in UCj and in classes of Pi, to the total number of methods in UCj. Mj(Pi) is calculated as:

$$\boldsymbol{Mj(Pi)} = \frac{\boldsymbol{M(UCj,Pi)}}{\boldsymbol{M(UCj)}} [20]$$

Where M(UCj,Pi) is the number of methods for UCj in Pi, and M(UCj) is the total number of methods in UCj. The value of Mj(Pi) ranges from 0 to 1.

Thus, the entire method offering of a given package Pi can be computed as the average of method offering measures for all UCs have method intersection with Pi:

$$\boldsymbol{AvgM(Pi)} = \frac{\sum_{j=1}^{n} \boldsymbol{Mj(Pi)}}{\boldsymbol{n}} [20]$$

Where n is the number of UCs supported by package Pi.

Degree of UC coverage of package Pi can be computed as the weighted sum of the two subcomponents facors, I(UCi) and M(UCi), as:

$$\boldsymbol{Degree\ of\ UC\ coverage\ of\ Pi = wI \times AvgI(Pi) + wM \times AvgM(Pi)} \ [20]$$

Where wI and wM are the weights of the UC's interaction and method offering, respectively, where wI, wM [[0, 1] and wI + wM = 1.

3.1.2 Degree of class relevancy

Class relevancy is formulated as a composition of two lower level factor: class functionality (CF) and class utilization (Util).

consider two classes C1 and C2. Let UC1 and UC2 be two sets of UCs that uses C1 and C2, respectively. If |UC1 ∪ UC2| and |UC1 ∩ UC2| the cardinality of the union and intersection of both sets respectively, then, we can define class functionality between two classes C1 and C2 as:

$$CF(C1,C2) = \frac{|UC1 \cap UC2|}{|UC1 \cup UC2|}[20].$$

Where a CF value of 0 indicates no common UCs shared by the two classes and a value of 1 indicates that both classes support the exact same UCs.

Therefore for a given class Ci in package Pk, the average CF, AvgCF can be computed as:

$$AvgCF(Ci) = \frac{\sum_{j=1}^{n} CF(Ci,Cj)}{n-1}[20]$$

Where n is the number of classes in Pk and Cj, $1 \leq j \leq n$, belongs to Pk.

The second factor that composes the degree of class relevancy is Util. This measures the degree of utility of a class by computing the percentage of methods of the class that make call(s) within the package. Given class Ci in package Pk, Ci utility can be computed as:

$$Util(Ci,Pk) = \frac{\#\ of\ methods\ in\ Ci\ interacting\ with\ methods\ in\ Pk}{\#\ of\ methods\ in\ Ci}[20]$$

The relevancy of class Ci in package Pk can be calculated as the combination of its CF and Util as:

$$CR(Ci) = wF \times AvgCF(Ci) + wUt \times Util(Ci,Pk)[20]$$

Where wF and wUt are the weights of the class functionality and class utilization, respectively.

Hence, degree of class relevancy of a package is computed as the average of the class relevancy for all classes in that package. Degree of class relevancy of package Pk is computed as:

$$Degree\ of\ Class\ relevancy\ of\ Pk = Avg(CR(Cj))$$ [20]

Now by aggregation of the previous formulas, the overall packaging quality, overallPackaging of the entire system is computed as average of all ***PackagingQlty*** each packages in the system:

$$OverallPackaging(system) = Avg(PackagingQlty(Pi))$$ [20]

Hence, from this formulation, the ***OverallPackaging*** should be maximized to achieve a higher quality packaging configuration.

Given a hypothetical sequence diagrams (SDs) shown in Fig. 10, Fig. 11 , and Fig. 12 with a sample configuration shown in Fig. 9, the overallPackaging(system) can be calculated as shown in Table 2. All weights being set to 0.5. More detail of how the calculations are arrived at is given by Ebad and Ahmed [20].

Table 2: showing calculation of overall packaging of the system

	P1	P2
PackagingQlty	0.5 (0.5) + 0.5 (0.72) = 0.61	0.5 (0.41) + 0.5 (.6) = 0.51
OverallPackaging	(0.61 + 0.51)/2 = 0.56	

Fig. 9: Sample configuration with 2 packages P1 and P2

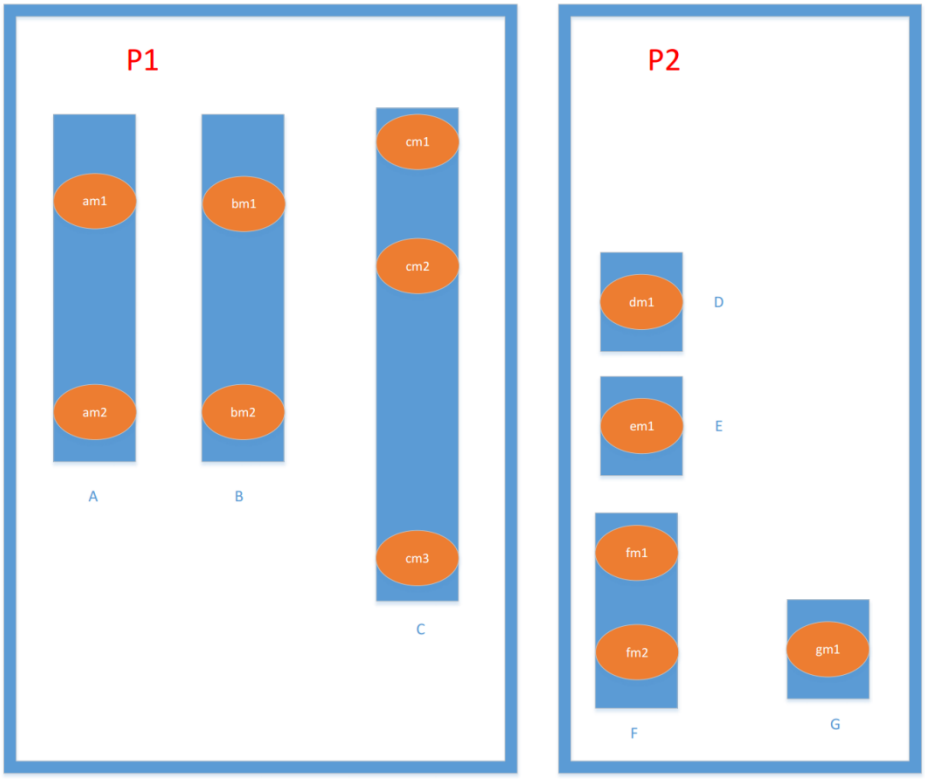


Fig. 9 illustrate a configuration of the hypothetical case study system illustrated through sequence diagrams in Fig. 10, Fig. 11, and Fig. 12. This configuration has 2 packages P1 and P2. Package P1 has 3 classes A, B, and C which respectively have methods am1, am2, bm1, bm2, cm1, cm2 and cm3. Package P2 has 4 classes D, E, F, and G which respectively have methods dm1, em1, fm1, fm2, and gm1.

Fig. 10: UC1 being realized by SD

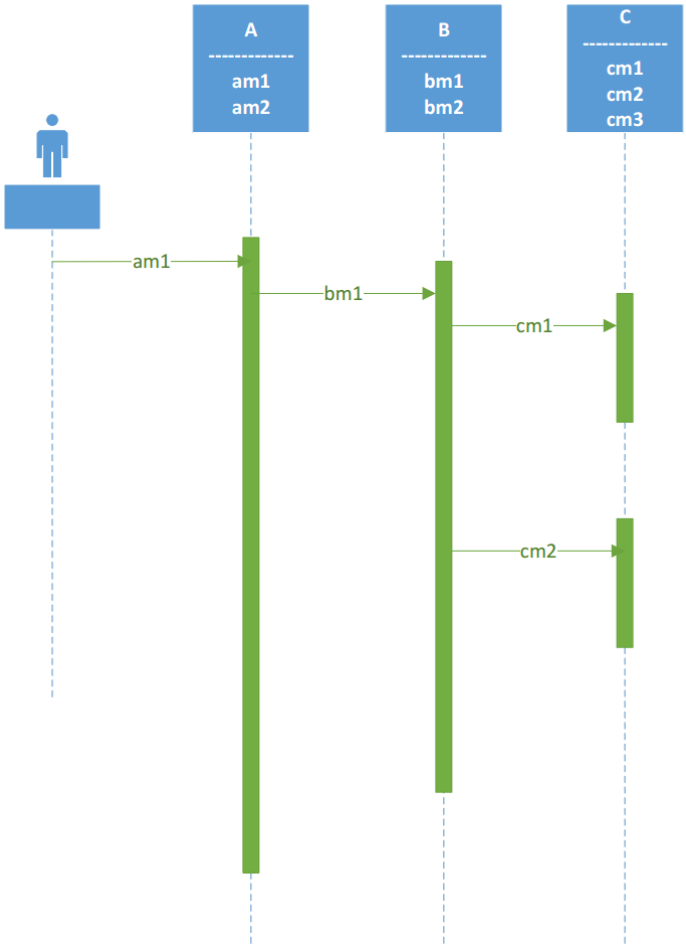


Fig. 10 illustrates the sequence diagram (SD) of the hypothetical system involving sequence of communications between methods of 3 different classes (A, B, and C respectively) of the hypothetical system.

Fig. 11: UC2 being realized by SD

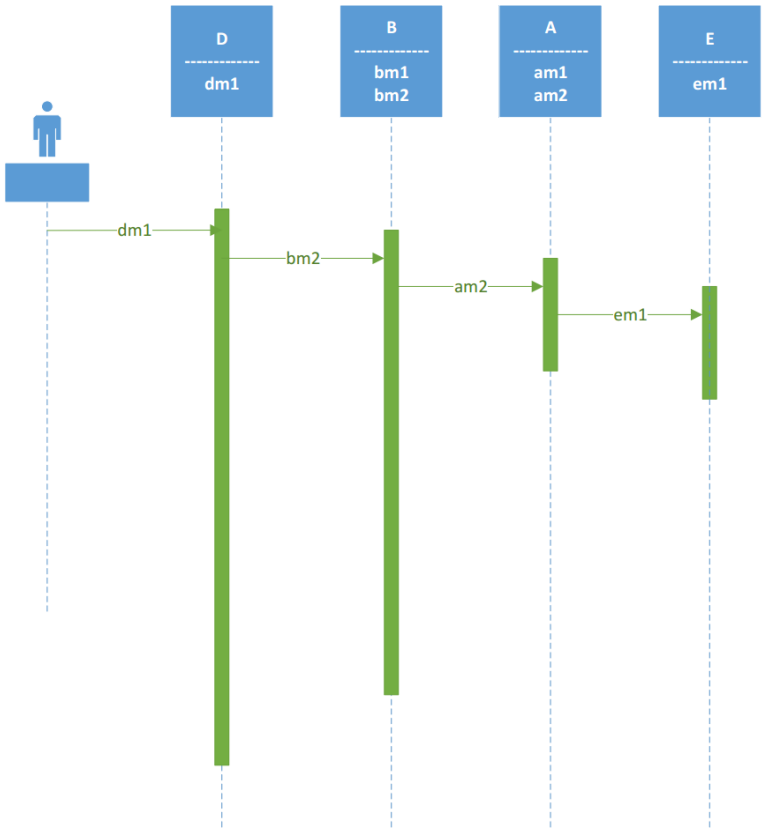


Fig. 11 illustrates the sequence diagram (SD) of the hypothetical system involving sequence of communications between methods of 4 different classes (D, B, A, and E respectively) of the hypothetical system.

Fig. 12: UC3 being realized by SD

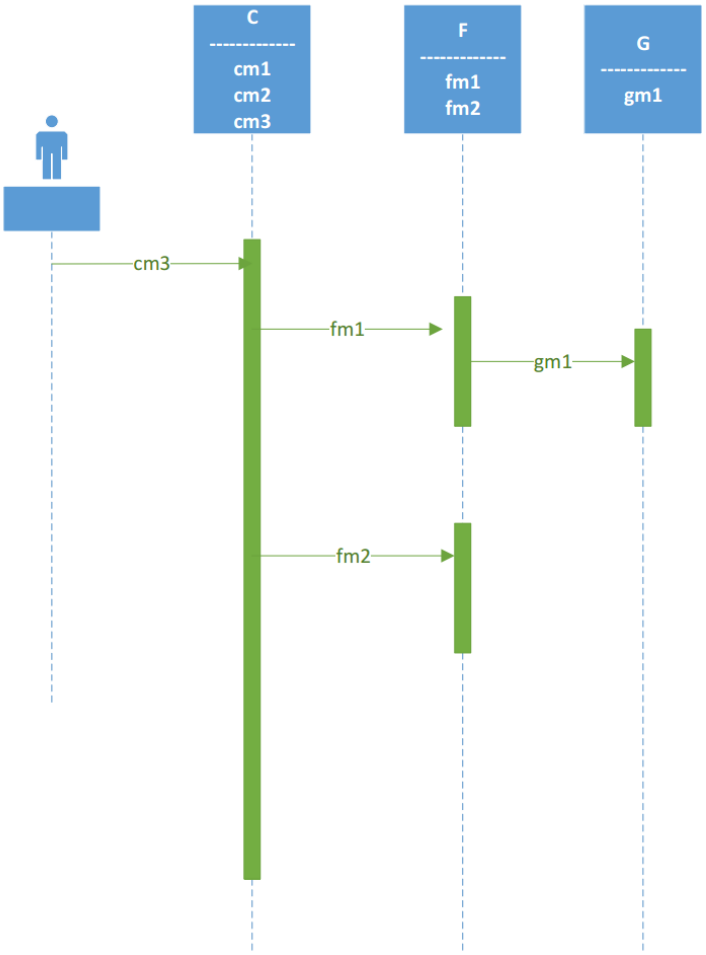


Fig. 12 illustrates the sequence diagram (SD) of the hypothetical system involving sequence of communications between methods of 3 different classes (C, F, and G respectively) of the hypothetical system.

3.2 Problem solving

3.2.1 Model extension

Outlined earlier were steps to be taken to identifying, analyzing, formulating and solving an optimization (multi or single objective) problem. This will serve as a guide for research pursuing this endeavor.

It is clearly showed ways in which an objective function can be formulated. I have shown clearly the relationship between machine learning and optimization. Helping new and novice researchers understand what they mean and how they relate.

I have provided a neural network interpretation of the original model successful model and thereby showed a clear path for feature research in automation of quantification and qualification of software artifacts. This has pave way for applying and investigating several neural network techniques in for packaging software systems.

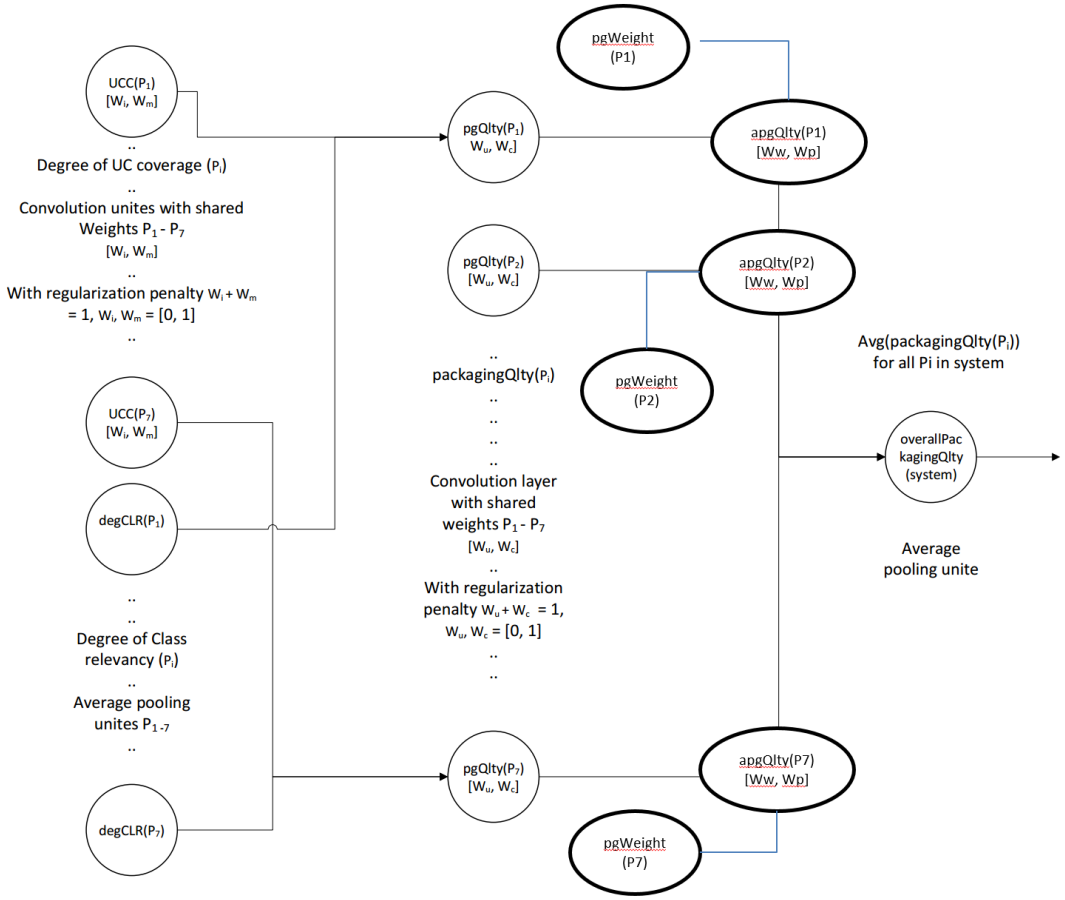
This way we can acquire simple metrics and formulate different architecture of neural networks then train them by using a training and validation dataset.

Consequently, neural network technique can be applied to other software engineering by acquiring simple software metrics from good knowledge of metrics formulation or simply by use of metric tools one can be able to develop a model for automatic quantification or qualification of software artifacts.

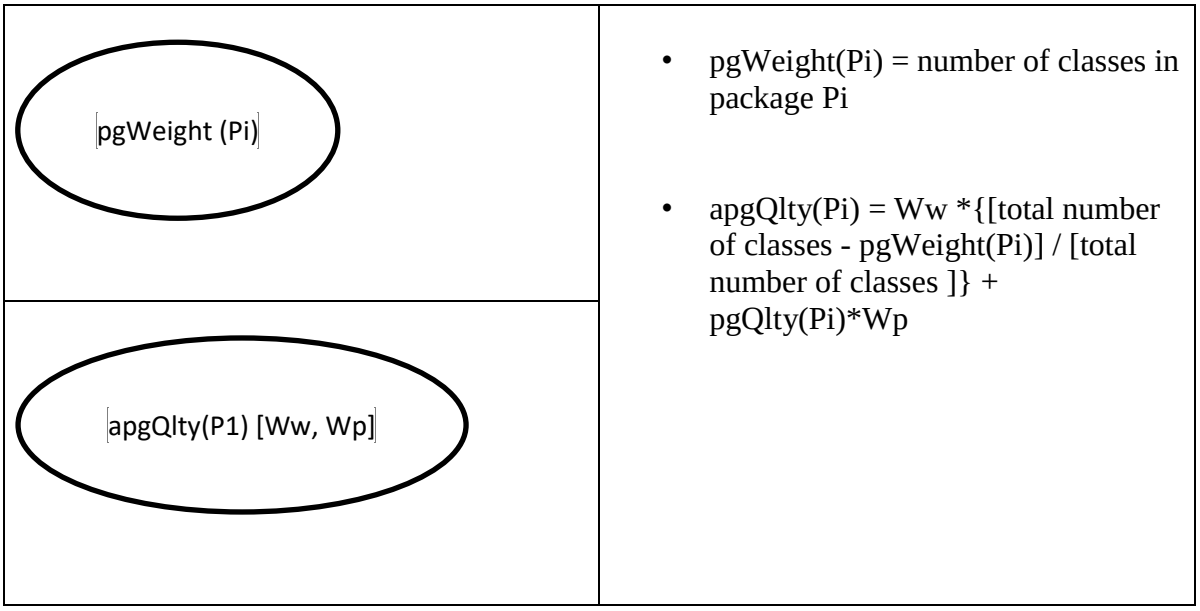
This study helps to further strengthen and demonstrate the justification and popularity of neural networks as current state-of-the-art in modeling.

So the lesson is, we should spend effort formulating latent features that are complicated (and even incomprehensible that we even run out of how to name them) instead acquire direct features as many of the direct features and let the neural network learn the higher level feature by itself.

Fig. 13: Convolution Neural Network model interpretation and extension



pgWeight (Pi), apgQlty(P1) [Ww, Wp]



3.2.2 Solution representation.

The problem at hand is a combinatorial optimization problem and so solutions of the problem have no sense of order. Moreover, we have to take note that numbers are only used to label the solutions. Solution representation is . The solution representation may result in redundant solutions. It also affects the difficulty of solving and reasoning about the problem based on the nature of constraints imposed on the representation. however redundancy has its advantage.

The use of some algorithms is dependent on the representation of the solution. Below is how the solution representations used in this work evolved.

49 dimension binaries. This representation can be imagined as a 7x7 matrix where each row represent a package and each column represent a class. The entries can only be 0 or 1. However, there is a constraint that the number of 1's in each column must be equal to one. There for custom genetic operators are required for this representation. We can number the

rows from top-down and columns left-right. This representation produces redundant configurations. For example a solution with all 1's in row one is same as solution with all ones in any other rows.

	$c1$	$c2$	$c3$	$c4$	$c5$	$c6$	$c7$
$p1$							
$p2$							
$p3$	1	1	1				
$p4$				1	1	1	1
$p5$							
$p6$							
$p7$							

7 dimensions of integers. This representation evolved from the previous one where each dimension represents a class from the columns of the previous representation. The value for the variable of a dimension comes from the row number of where 1 appears in that column. So this can be used with algorithms that accept integer or real dimensions. For real variable type, we have to round the value to a feasible integer. The constraints in this case are min and max bounds that simpler than to enforce and assimilate than in the earlier representation. It suffers from same redundancy as earlier.

$c1$	$c2$	$c3$	$c4$	$c5$	$c6$	$c7$
3	3	3	4	4	4	4

1 integer rounded to boundaries. If we view the earlier representation as a 7 digits integer then, we can represent our solution with a single 7 digits integer between 1111111 to

7777777. In this case, the constraint will be that integers in the range with any digit other than from 1 to 7 constitute an invalid solution. For real variable type, we have to round the value to a feasible integer to impose the constraint is not easy. One way to do it is that whenever you have a 0 value digit it should be rounded to 1 and whenever you get 8 and 9 they should be rounded to 7. However, this has a problem as it is not consistent in ordering of solutions. A question one may ask is how problem with 10 or more variable values can be represented. This solution is to use a number base system to can take all the values of a variable. It suffers from same redundancy as ealier first representation. Illustrate the problem and explain why no need for the experiment.

1 integer array of all configurations. This solution representation evolved due to the rounding problem of the earlier representation. So in this representation all valid configurations are computed an stored in and array. It suffers from same redundancy as earlier first representation. This may not be feasible if we have real dimension unless if discretized or if the dimension of solution is very high it may also be infeasible to compute.

1 integer array of all configurations with elimination of repeated configurations. The computation required to do this is not feasible in real application scenario because the complexity is high. Give the algorithm to do it and the complexity analysis here. However this representation will still be utilized for this case study scenario since the number of it is relatively small. Using this helps make some analysis faster. This will be demonstrated later on when analysing the penalty function or new objective formulation. Moreover since the same solution is repeated many times the algorithm may be lucky to fine one out of many.

Number of packages and constrained 7 dimensions based on number of packages. This imposes a very harsh and difficult to maintain nonlinear constraint. Since this imposes a nonlinear constraint, readymade genetic operators in the toolbox cannot be used to achieve valid solution after each iteration. The variable number of packages make it difficult to implement the crossover operators.

3.2.3 Architectural stability

Attempt was made to validate the metric using architectural stability metric. This validation concept stems from an intuition that a well packaged software should be more stable and be averse to too many changes. A metric by Ebad and Ahmed [19] called Architectural Stability Metric (ASM) was considered for this task. ASM is metric purely based on inter-package connections. Afterwards, extension was made to ASM called Extended Architectural Stability Metric (ExASM) that considers both changes intra-package and inter-package connections. Another metric CEAM (Coupling Efferent-Afferent Metric), based on package instability metric proposed by Robert C Martin in his book [43], was also used in this endeavor.

Formulation of both ASM and ExASM is outlined below:

- If R1 and R2 are two releases having two packages P1 and P2.
- Let:
  - A_{inter} and A_{intra} be the set of added inter-PCs and Intra-PCs in R2,
  - D_{inter} and D_{intra} be the set of deleted inter-PCs and intra-PCs from R1
  - O_{inter} and O_{intra}be the set of original inter-PCs and intra-PCs that exist in R1
  - ASMinter be inter-package ASM

  - ASMintra be intra-package ASM

- ExASM(R1,R2) = w* ASMinter (R1,R2) + (1-w)* ASMintra (R1,R2)
- Where:
  - w is user specified weight that balances between inter-PC and intra-PC
  - ASMinter = $\frac{|O_{inter}|-|D_{inter}|}{|O_{inter}|+|A_{inter}|}$
  - ASMintra = $\frac{|O_{intra}|-|D_{intra}|}{|O_{intra}|+|A_{intra}|}$
- ASM as formulated by Ebad and Ahmed is simply ASMinter as defined above.
- The proposed ExASM metric is theoretically validated and satisfies the seven listed mathematical properties as follows.
  - Non-negativity: It can be seen very easily that the metric as stated satisfies this property.
  - Normalization: The metric values clearly ranges between 0 and 1. The metric will give 0 if no changes occur and will give 1 if there's complete change. That is the metric should have a clearly defined upper and lower bounds
  - Null value: This properties should hold in the case where there exist no inter-PC and intra-PC between the two versions at all. This property is satisfied with ExASM metric when both sets O_{inter} and O_{intra} are empty, Implying, no PCs in Ri (the base release) in the first place.
  - Maximum value: This property is also clearly satisfied and correspond to the upper bound of normalization property
  - Transitivity: This property ensures consistency of the metric evaluation. In case where this are 3 different stability measures, then, if the 1st meausure is better than the 2nd and the 2nd is better than the 3rd, then the 1st should be better than the 3rd.

Formulation of Coupling Efferent-Afferent Metric (CEAM) is given as follows:

- Afferent couplings (Ca): this measures the dependency of a package in inwards by counting the number of classes that outside of the package that depend on the classes within the package.

- Efferent couplings (Ce): this measures the dependency of packages outwards by counting the number of classes inside the package that depend on some other classes outside of the package.
- Instability (I) can be thus defined as:
  - I = Ce / (Ce + Ca).
  - The highest value that can be scored by this metric is 1 and the lowers is 0. When I = 0 then this signifies a perfectly stable package and when I=1 then it signifies an entirely unstable package.
- Stability(S) of a package = 1 – Instability

Then, stability of the overall system was as CEAM:

- CEAM Stability of system = average of all S of all packages

CHAPTER 4

EMPIRICAL VALIDATION RESULTS

4.1 Experiment Setup and Design

4.1.1 System and platform

MATLAB® 2010b platform was used for all experiments. Running it on Windows 8.1 Pro operating system on MacBook Pro (Retina, 13-inch, Early 2013) (2.6GHz dual-core Intel Core i5 processor (Turbo Boost up to 3.1GHz) with 3MB shared L3 cache).

The GA algorithm can be found as toolbox on MATLAB. The MATLAB GA toolbox was used to harness the features of the toolbox such as algorithm's progress data collection and visualization. MATLAB random number generator is reseeded at the command line at every MATLAB session involving the experiment to ensure good randomness since all the OA used employ random number.

4.1.2 Experiment parameters

As discussed earlier, the original model has 8 model parameters:

1. wU is the weight of the UC's coverage in a package ,
2. wC is the weight of the class relevancy in a package,
3. wI is the weight of the UC's interaction,
4. wM is the weight of method offering,

5. wD is the weight of direct interactions,
6. wT is the weight of indirect interactions,
7. wF is the weight of class functionality, and
8. wUt is the weight of class utilization.

4.1.3 Experiment design

Each instance of experiment was run 5 times (replications) so that the average output is calculated as the result of that instance. Since grid search technique was used, numerical value factors have to be discretized as all possible values cannot be tried. Even after discretization, a full factorial design with replication will be too large. Therefore, a fractional factorial design of $n2^m$ has to be used. However fractional factorial design is not used to scale down the number of factors but to manually monitor how the changes in parameter values affect result so we can have an idea about where a good set of values of the parameters are.

4.2 Solution representation experiments

This was done as a preliminary experiments to decide what solution representation are suitable. A single algorithm is enough to determine what solution representation is suitable. GA was used for this task. The preliminary experiment is important to rapidly scale down the number of experiments (run of algorithms).

As part of the preliminary experiment, analysis of the brute force algorithm is given. We need to know attribute of the brute force algorithm so that we can compare and appreciate the effort of the optimization algorithms. Number of function evaluation for the brute force

is at least number of configurations in 7 integer solution representation because all points have to be evaluated at least once. It took 49815.628 seconds (approximately 14 hours) to run the algorithm. When running the brute force algorithm, the score of each configuration was saved to a permanent memory to be reused later so that it doesn't have to be calculated at every function evaluation and thereby saving experiment time. Below is the plot of the overallpackagingQlty against solutions.

The original model with model parameters set to (wU = 0.5; wC = 0.5; wI = 0.25; wM = 0.75; wD = 2/3; wT = 1/3; wF = 0.85; wUt = 0.15) was used in this experiment. These parameter values are those recommended by Ebad an Ahmed [20] for getting intuitive packageing. We used these setting because we do not want the optima to be at the boundary as it will be if model is used as it is and parameter values are all set to 0.5 except for wD = 2/3 and wT = 1/3. Having optima points at the boundary does not help assess effectively the performance of an OA.

GA with integer constraint was the only OA used in this case. The algorithm GA toolbox uses for integer constraint optimization is based on the work of kusum et al. [13] In this case, GA does not allow selection or specification of creation, crossover and mutation functions. So the only 2 options necessary to tune are number of elites and crossover fraction.

To illustrate the performance of each representation format, 2 media are used:

1. Table of average of best scores for the 5 runs of each instance combination of the parameters.

2. the graph plots during an optimization process with values of parameters set to those that give the best average score.

We should keep in mind that the score with the lowest value is the best. This is because in Matlab toolbox, the problem as to be formulated in terms of minimization. so the objective function as been negated. Therefore the best values on the plot and table are the minimum values.

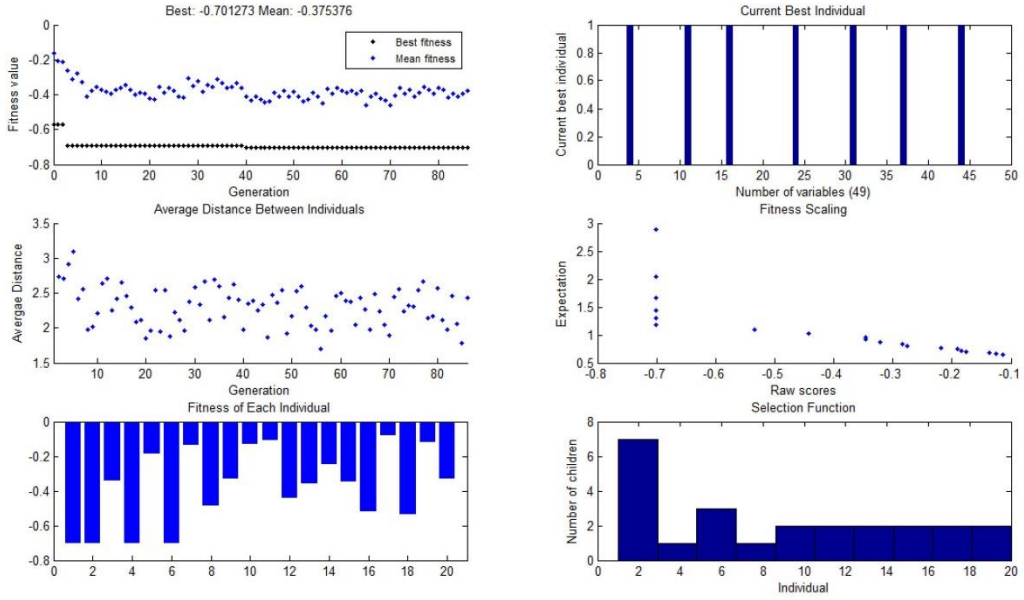
The results from this experiment will enable those who want to subsequently endeavor in optimization problem solving choose an appropriate representation.

4.2.1 49 bits representation

Table 3: 49 bits optimization result

Instance	Number Elites	crossover Fraction	mutation Ratios	Avrg score	Best score
1	**2**	**0.8**	**0.8**	**-0.70207**	**-0.71557**
2	**2**	**0.8**	**0.2**	**-0.67591**	**-0.71557**
3	**2**	**0.2**	**0.8**	**-0.70985**	**-0.71557**
4	**2**	**0.2**	**0.2**	**-0.62973**	**-0.70127**
5	**12**	**0.8**	**0.8**	**-0.64124**	**-0.71557**
6	**12**	**0.8**	**0.2**	**-0.60799**	**-0.71557**
7	**12**	**0.2**	**0.8**	**-0.67586**	**-0.70156**
8	**12**	**0.2**	**0.2**	**-0.66767**	**-0.70156**

Fig. 14: 49 bits optimization result

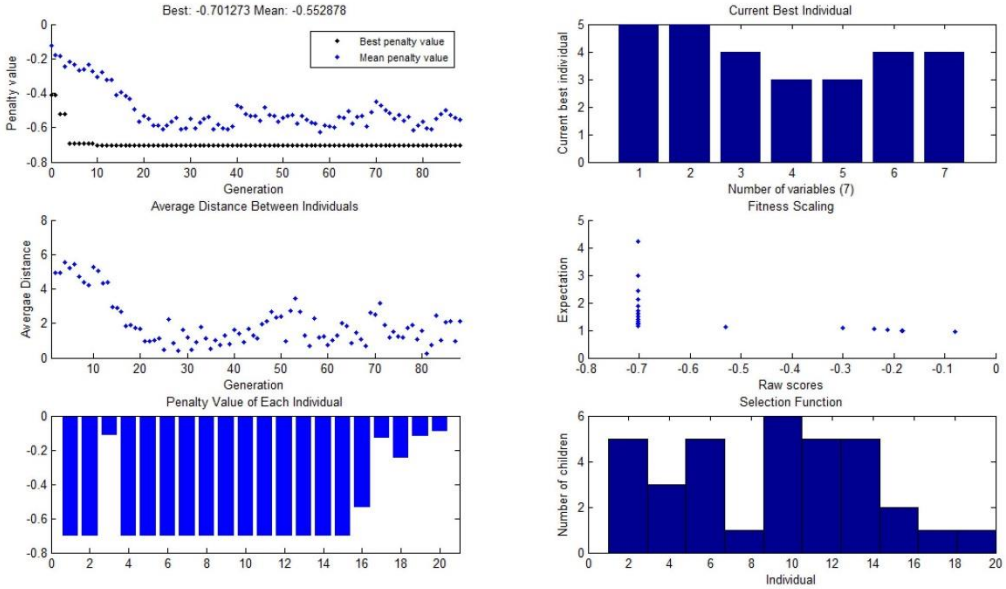


4.2.2 7 integer representation

Table 4: 7 integer optimization result

Instance	Number Elites	crossover Fractions	avrg score	best score
1	2	0.8	-0.71128	-0.71557
3	2	0.2	-0.66457	-0.71557
5	12	0.8	-0.62742	-0.71557
7	12	0.2	-0.68419	-0.71557

Fig. 15: 7 integer optimization result

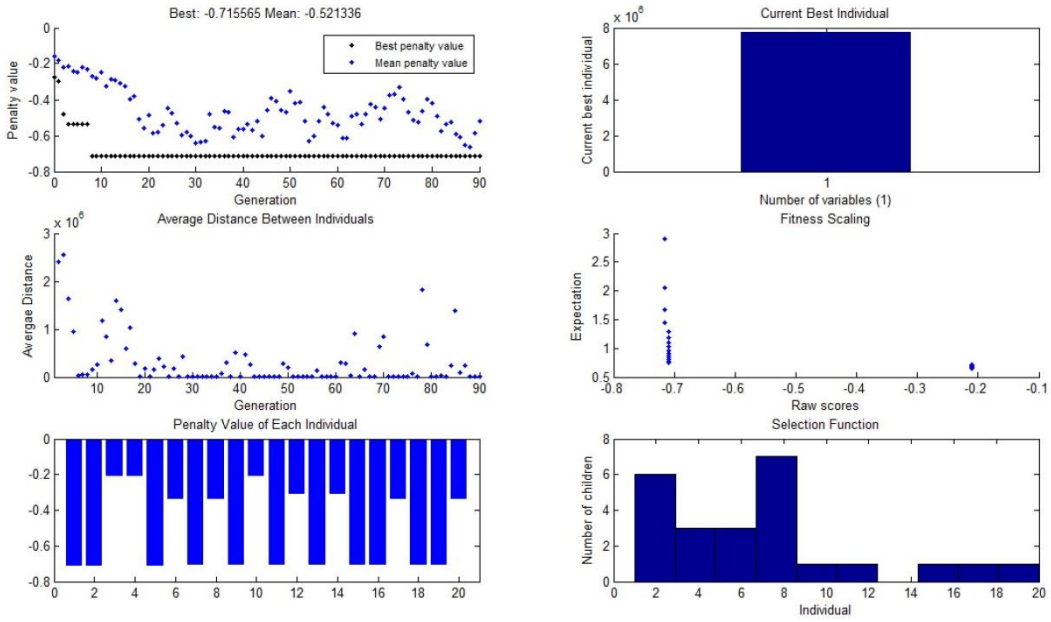


4.2.3 1 integer rounded

Table 5: 1 integer optimization result

Instance	Number Elites	crossover Fractiions	Avrg score	Best score
1	2	0.8	-0.63527	-0.71557
2	2	0.2	-0.69801	-0.71557
3	12	0.8	-0.62092	-0.70127
4	12	0.2	-0.64969	-0.71557

Fig. 16: 1 integer optimization result



4.2.4 1 integer configuration array

Table 6: 1 integer confic array optimization result

Instance	Number Elites	crossover Fractions	Average score	Best score
1	2	0.8	-0.64375	-0.70156
2	2	0.2	-0.67946	-0.71557
3	12	0.8	-0.54344	-0.70127
4	12	0.2	-0.64619	-0.70156

Fig. 17: 1 integer confic array optimization result

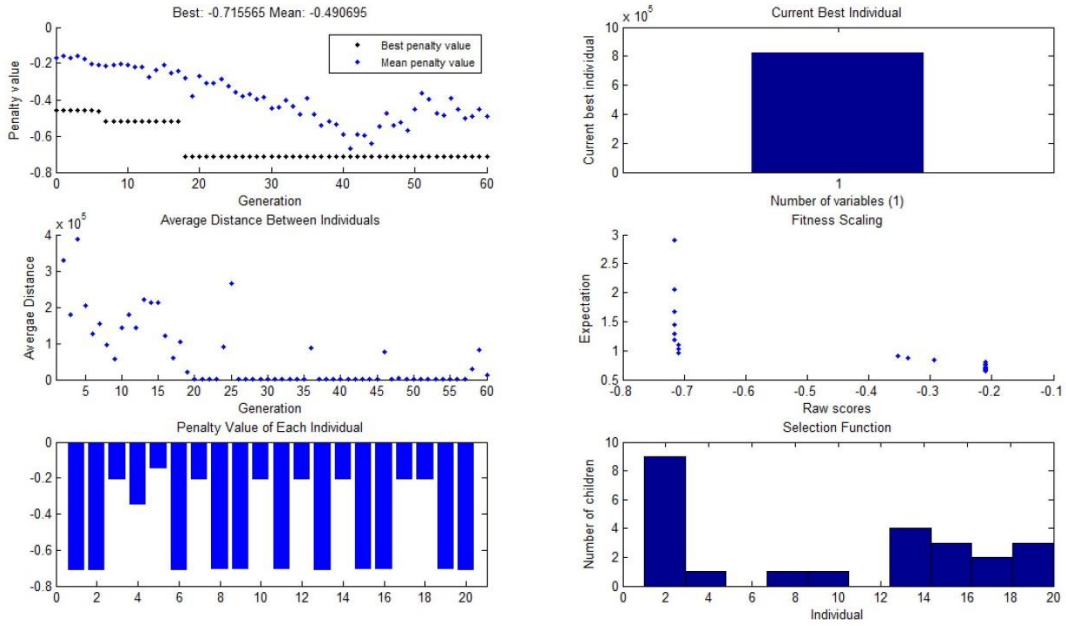


Table 7: average score comparison

representation	49 bits	7 integer	1 integer rounded	1 integer config array
average score	-0.70985	-0.71128	-0.69801	-0.67946

4.2.5 Discussion and conclusion: Solution representation

As it can be seen on Table 7, the 7 integer representation has the best score of all the four representation models.

4.3 Model evaluation experiment

4.3.1 Brute force analysis

Brute force which will be almost impossible on a real case study, however, will be used to learn parameter values that will give us solutions that have optimum value so we can have a good intuition about how well the proposed model is doing. However, even with the

miniature model (the hypothetical case study), the brute force will still take too much time. In this case, the solution representation with 1 integer with elimination of repeated configurations, becomes useful because it reduces the number of configurations to unique packages and thereby reducing brute force run time significantly.

- All configurations Brute force analysis
- Unique configurations Brute force analysis
- fitness Brute force analysis

All configurations Brute force analysis

- number of all configurations ($\mathrm{noclasses}^{\mathrm{noclasses}}$) (for 7 classes 823543)
- algorithm complexity to get all configurations Omega(n^n)
- time it takes to make all configurations
    - for 7 classes 1.1289 secs
    - For 50 classes 3.1825e+77

Unique configurations Brute force analysis

- number of unique configurations
    - no way estimated by Gaussian
    - for 7 classes 877 by brute force
- time it takes to make unique configurations

- was not recorded
- But relatively takes time

– algorithm complexity to get unique configurations (nlogn)

Combinatorial analysis of unique configurations

- Brute force 7 classes data was used
- Number of genotypes of a given phenotype with n number of packages is Permutation (N,n). Where N is total number of classes.
  – E.g. n = 2, 42.

Table 8: Number of genotypes of a given phenotype with n number of packages

n	1	2	3	4	5	6	7
Number of genotypes	**7**	**42**	**210**	**840**	**2520**	**5040**	**5040**

- Number of phenotypes with given number of packages n
- No analytical way
- Spent time analyzing and looking for a pattern but couldn't come up with a formula for it.
- Computed by brute force

- Moreover, having idea of this numbers is helpful for initial population creation.

Table 9: Number of phenotypes with given number of packages n

n	1	2	3	4	5	6	7
Number of phenotypes	**1**	**63**	**301**	**350**	**140**	**21**	**1**

- Estimation of number of phenotypes with given number of packages n

Fig. 18: Estimation of number of phenotypes with given number of packages n (1)

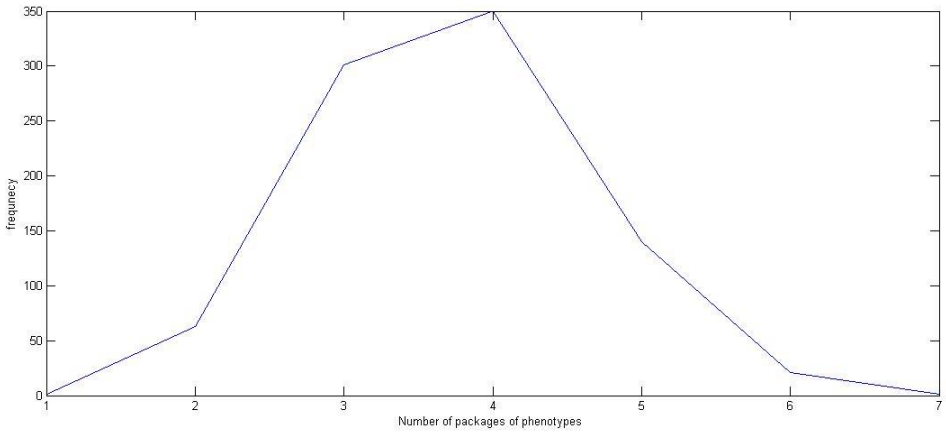
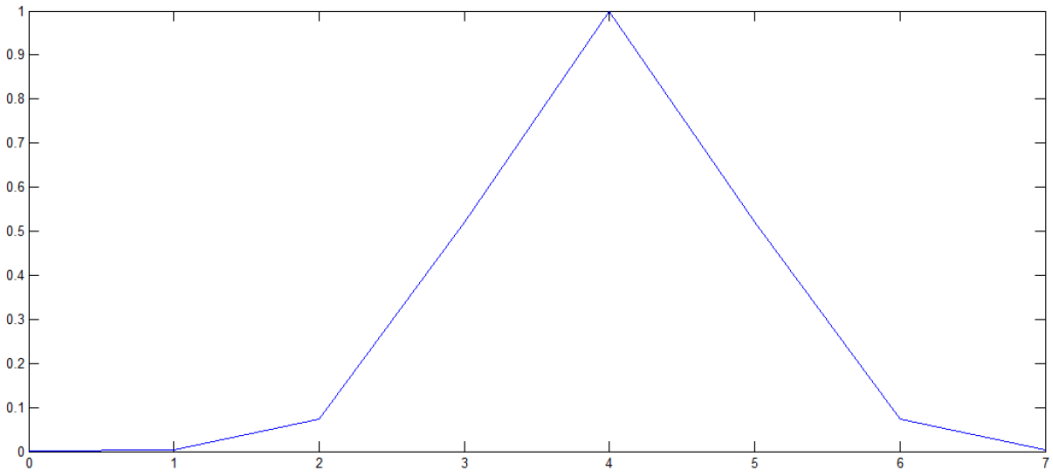


Fig. 19: Estimation of number of phenotypes with given number of packages n (2)



Fitness Brute force analysis

- fitness Brute force analysis
  - Made brute force using with metric intuitive weights
  - time to make brute force (18.4375 hours)

Fig. 20: Graph of fitness function for all configurations

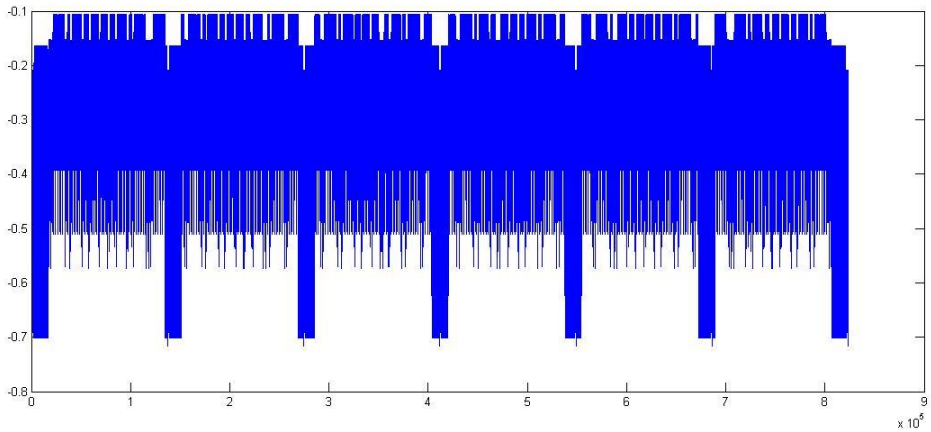


Fig. 21: Histogram of fitness values for all configurations

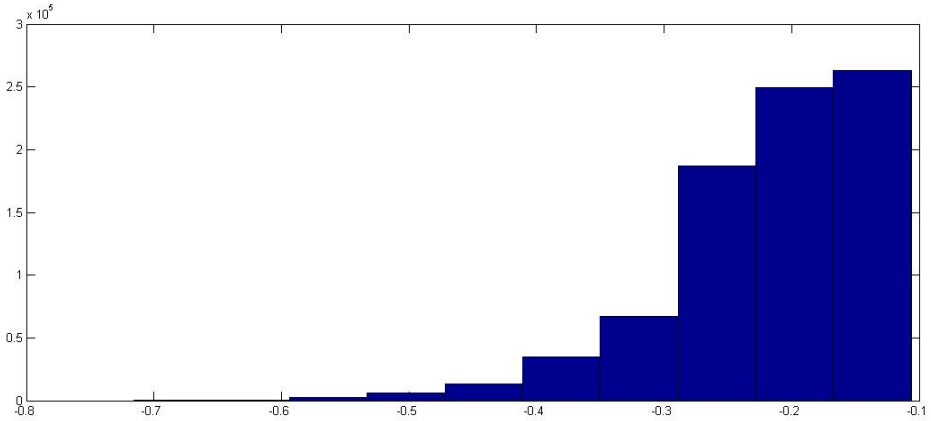


Fig. 22: Graph of fitness function for unique configurations

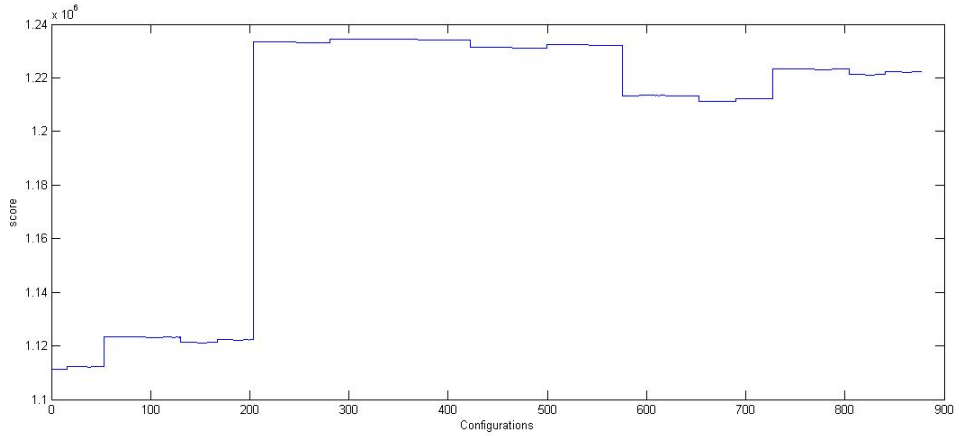
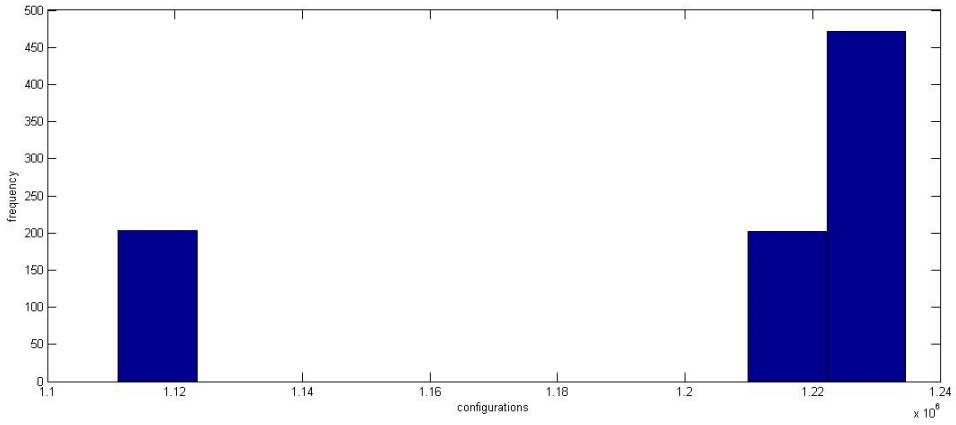


Fig. 23: Histogram of fitness values for unique configurations



4.3.2 Convolution Neural Network model evaluation

Expert's suggestion

In the work of [20] the configurations that were reported to march with experts suggestion are given in Table 10.

Looking at Table 10, there are two factors we have learnt about in all the configurations.

- number of packages
- associated classes

All the four configurations have 2 or 3 number of packages. So our suggested optima should have same or something very similar.

Looking at the table we also learned that certain classes are almost always packaged together. Classes A and B, D and E, and F and G. where it seems it doesn't really matter where C is.

Table 10: expert suggested rank compared with (Ebad & Ahmed, 2015) metric

configuration	Intuitive rank	Metric rank 1	Metric value 1	Metric rank 2	Metric value 2
ABDE, C, FG	**1**	**1**	**0.7190**	**7**	**0.5522**
ABCDE, FG	**2**	**2**	**0.7155**	**1**	**0.7156**
ABDE, CFG	**3**	**5**	**0.7015**	**3**	**0.7016**
AB, C, DE, FG	**4**	**3**	**0.7143**	**6**	**0.5893**
AB, CFG, DE	**5**	**6**	**0.7010**	**4**	**0.7013**
ABC, DE, FG	**6**	**7**	**0.6903**	**5**	**0.6907**
ABE, C, D, FG	**7**	**8**	**0.6690**	**8**	**0.4189**
ABD, C, E, FG	**7**	**8**	**0.6690**	**8**	**0.4189**
AB, C, D, E, FG	**8**	**9**	**0.6688**	**9**	**0.3687**
ABCDEFG	**9**	**4**	**0.7100**	**2**	**0.7099**
Spearman correlation coefficient		**0.79**		**0.3283**	

Fig. 24 gives a neural network interpretation of the Ebad metric [20] and also shows how the metric can be extended thereby. To be specific, the Ebad metric [20] can be seen specifically as a convolutional neural network because of the presence of convolutional layers.

Fig. 24: Convolution Neural Network model interpretation and extension

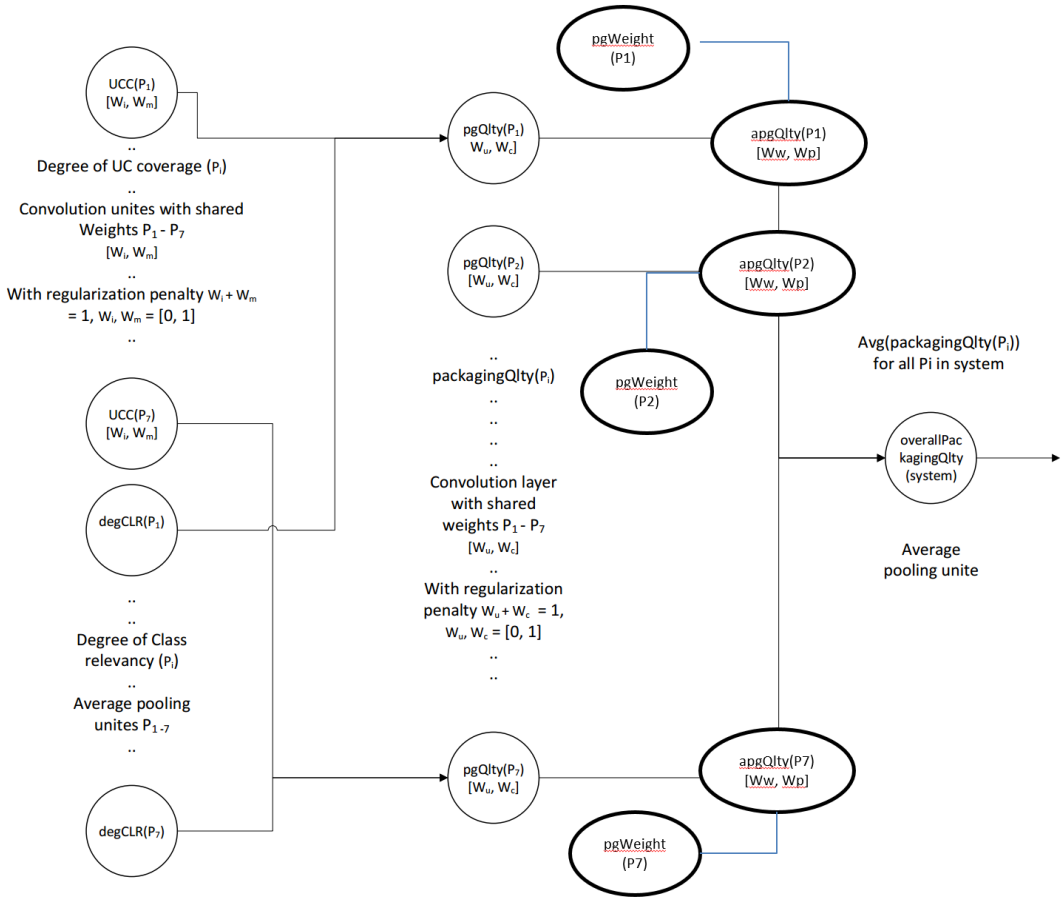


Fig. 25 give another view of the NN metric model where new features such as Weight(Pi), and WeightPenalty(Pi) can be added to all other features collected from earlier metric [20], AvrgMoff(Pi), AvergCI(Pi), and dgrCR(Pi).

Fig. 25: Convolution Neural Network model metric

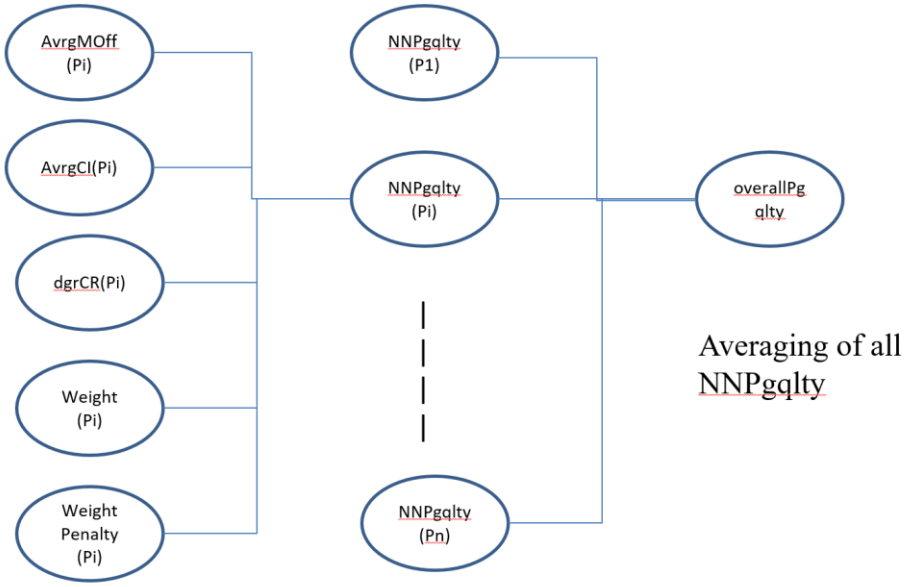


Table 11: CNN with linear activations unites

configuration number	P1	P2	P3	P4	P5	P6	overallPackagingQlty
1	ABCDEFG						-0.701
2	AB	CFG	DE				-0.701
3	AB	C	DE	FG			-0.589
4	AD	BCD	FG				-0.537
5	ABD	CE	FG				-0.522

Table 12: CNN with logistic activation unites

configuration number	P1	P2	P3	P4	P5	P6	overallPackagingQlty
1	AB	CFG	DE				-0.754
2	ABCDEFG						-0.597
3	ABE	CFG	D				-0.582
4	A	BDE	CFG				-0.446
5	AD	BE	CFG				-0.383

Discussion and conclusion: CNN model interpretation and extension

Table 11 shows result of using neural network implemented on Matlab NN toolbox to implement the Ebad metric. The network was implemented with all activation unites being linear activation function. The table shows the top 5 configurations from that implementation. For the matching configurations, on both Table 10 and Table 11 the overallPackagingQlty score give the same value. As it can be seen for the case of configuration ABCDEFG, AB, CFG, DE and AB, C, DE, FG.

Table 12 shows result of using neural network implemented on Matlab NN toolbox. The network was implemented with all activation unites being logistic activation function. Logistic activation function is what is widely used in conventional neural network implementation. The table shows the top 5 configurations from that implementation. This was experiment was conducted to illustrate that the metric can be interpreted as neural networked and extended thereby.

Hypothesis 1: The metric used by Ebad and Ahmed [20] can be reinterpreted and extended to make a better software packaging metric. This hypothesis has been partially fulfilled by an interpretation of the metric as convolutional neural network and extension of the metric

through that interpretation. The other part of the hypothesis, hypothesizing a better metric, is not confirmed by the scope of experiment done. This can be done in later works.

4.3.3 Packaging metric correlation with ASM, ExASM, and CEAM

Attempt was made to check if there's correlation between the packaging metric and architectural stability metrics (ASM, ExASM, and CEAM). The first experiment in this category was an attempt on checking correlation of ASM to PackagingQlty metric. Then later on correlation with ExASM was checked. Further correlation check was then made with CEAM.

Hypothetical case study

Given the UC diagrams of the hypothetical case study system in Fig. 26 (shown earlier in Fig. 10, Fig. 11, and Fig. 12).

- Hypothetical case study with configuration: [1 1 1 1 1 2 2] [ABCDE, FG] shown in Fig. 27.
- This is the best configuration of this system using Ebad metric and intuitive parameters

Fig. 26: Hypothetical case study system UC diagrams

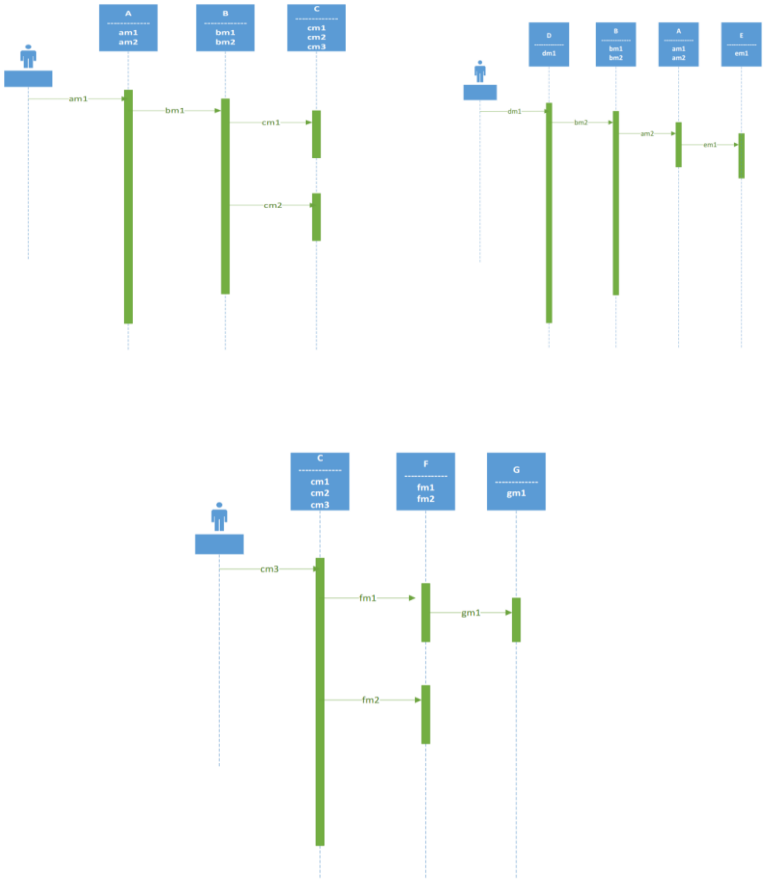
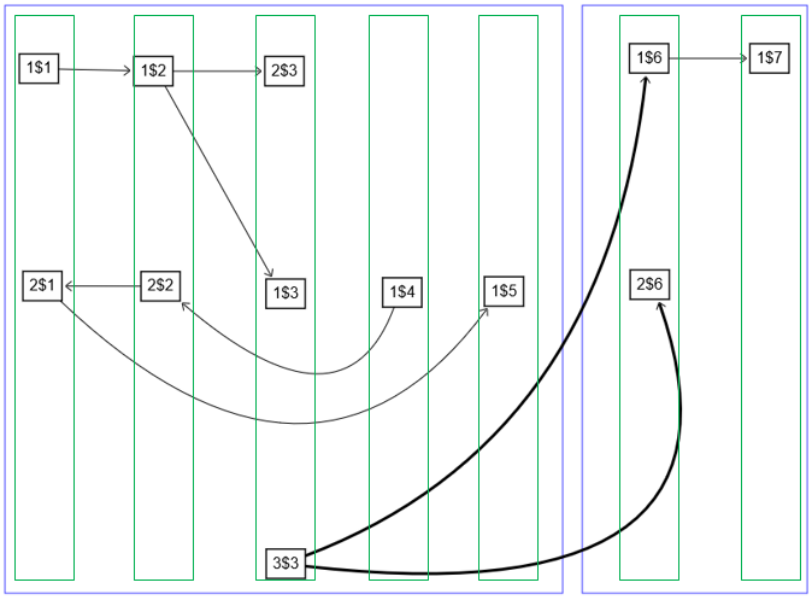


Fig. 27: Best configuration of the hypo. Case study system using Ebad metric and intuitive parameters



Nine cases of changes to the hypothetical case study were investigated:

- Case 1: ASM, ExASM and CEAM of v1.1 and v1.1
- Case 2: adding an inter-package call into V1.1 to make V2.1
- Case 3: adding an intra-package call into V1.1 to make V3.1
- Case 4: deleting an inter-package call from V1.1 to make V4.1
- Case 5: deleting an intra-package call from V1.1 to make V5.1
- Case 6: adding a class making inter-package call into V1.1 to make V6.1
- Case 7: adding a class making intra-package call into V1.1 to make V7.1
- Case 8: deleting a class making inter-package call from V1.1 to make V8.1
- Case 9: deleting a class making intra-package call from V1.1 to make V9.1

The detailed figures demonstrating all these cases can be found in

Appendix 1 from Table 33 to Table 75**.**

The nine cases were also used to tune the weight parameter called Weight of ExASM. Eleven values of Weight ranging from 0 to 1 with 0.1 intervals. Change in packaging quality (ChangeInPgQlty) was plotted against ExASM for the eleven values. The highest absolute correlation coefficient (corr. Coef.) recorded is 0.7053 when value of Weight is set to 0.4. The correlation figure for Weight = 0.4 is shown in Fig. 32. The figures showing results for other values of Weight can be seen in Fig. 28, Fig. 29, Fig. 30, Fig. 31, Fig. 33, Fig. 34, Fig. 35, Fig. 36, Fig. 37, and Fig. 38.

The corr. coef. R, is quiet close for almost all the different values of Weight. This can be seen on table Table 13. For Weight value 0 corr. coef. is 0.43118 as shown in Fig. 28. For Weight value 0.1 corr. coef. is 0.59118 as shown in Fig. 29. For Weight value 0.2 corr. coef. is 0.67436 as shown in Fig. 30. For Weight value 0.3 corr. coef. is 0.70276 as shown in Fig. 31. For Weight value 0.4 corr. coef. is 0.70530 as shown in Fig. 32. For Weight value 0.5 corr. coef. is 0.69801 as shown in Fig. 33. For Weight value 0.6 corr. coef. is 0.68777 as shown in Fig. 34. For Weight value 0.7 corr. coef. is 0.67726 as shown in Fig. 35. For Weight value 0.8 corr. coef. is 0.66743 as shown in Fig. 36. For Weight value 0.9 corr. coef. is 0.65857 as shown in Fig. 37. For Weight value 1 corr. coef. is 0.65068 as shown in Fig. 38.

To illustrate this point the average of all the corr. coef. is calculated as 0.6495 and the standard deviation is 0.005693. As it can be seen the standard deviation is quiet small indicating no much variation between the values of the corr. coef. This led us to conclude

that there may be no likely correlation between this ExASM and the packaging metric. So another architectural stability metric CEAM was considered.

Fig. 28: ChangeInPgQlty vs ExASM with Weight = 0

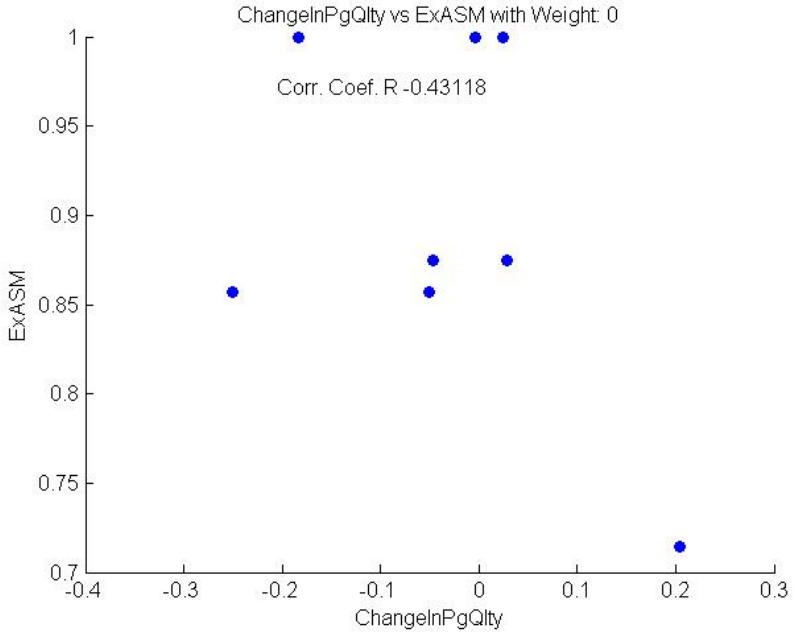


Fig. 29: ChangeInPgQlty vs ExASM with Weight = 0.1

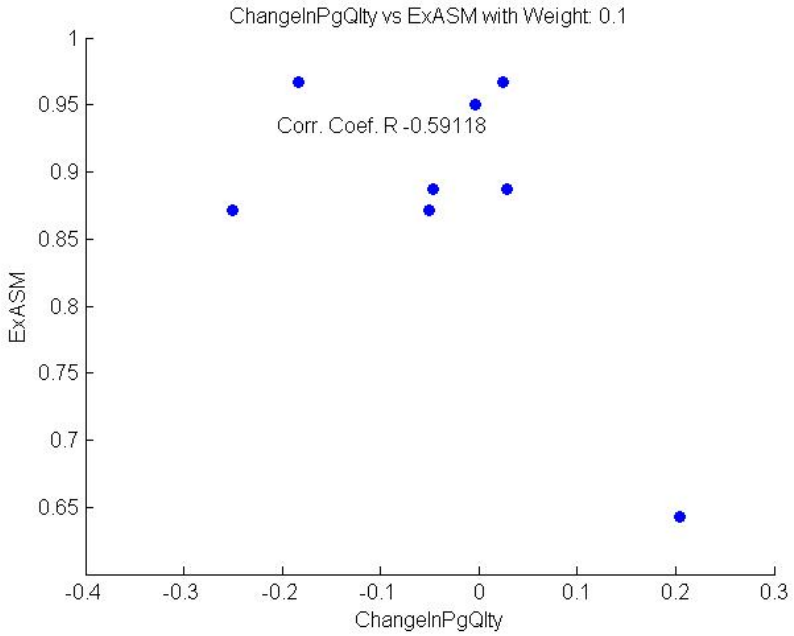


Fig. 30: ChangeInPgQlty vs ExASM with Weight = 0.2

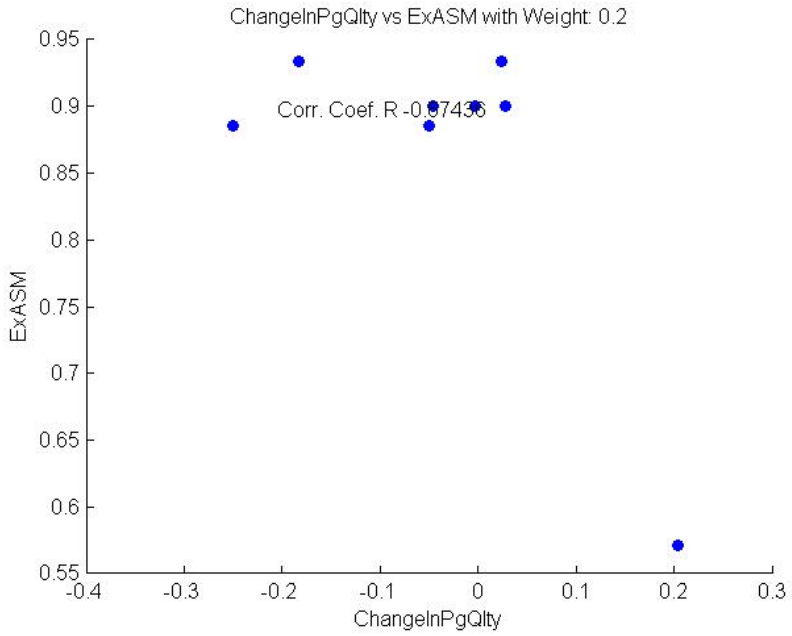


Fig. 31: ChangeInPgQlty vs ExASM with Weight = 0.3

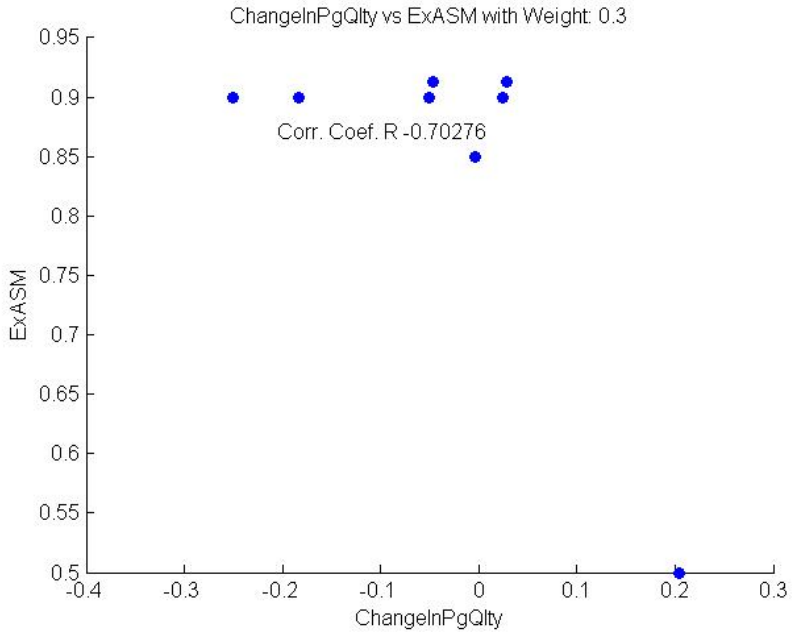


Fig. 32: ChangeInPgQlty vs ExASM with Weight = 0.4

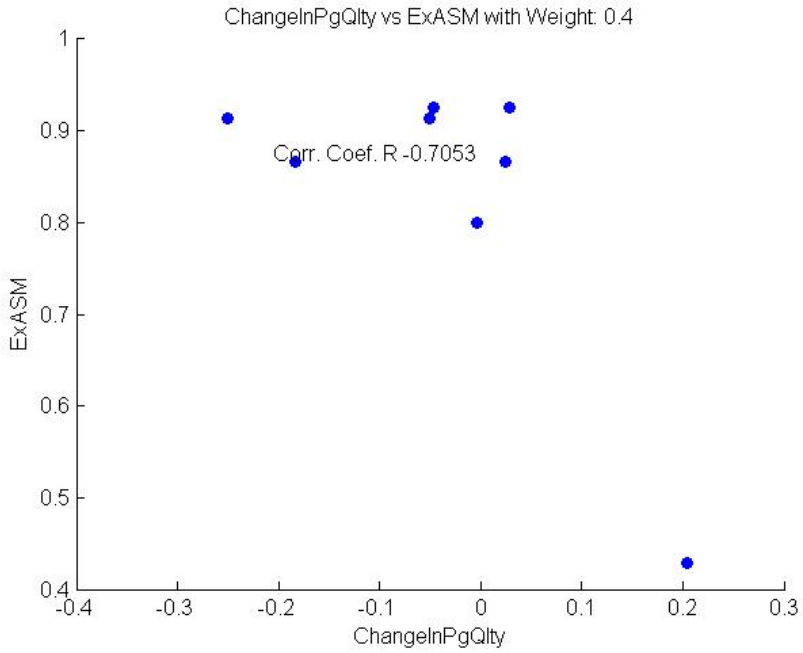


Fig. 33: ChangeInPgQlty vs ExASM with Weight = 0.5

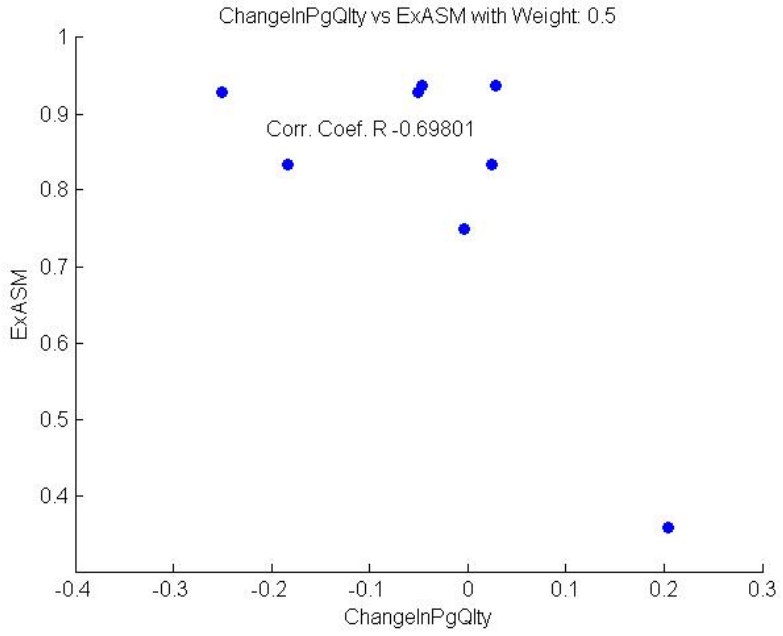


Fig. 34:ChangeInPgQlty vs ExASM with Weight = 0.6

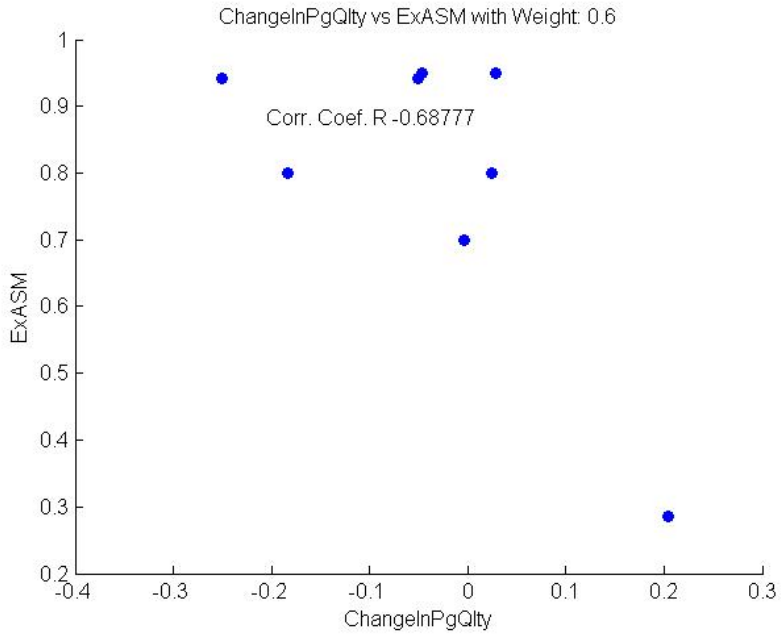


Fig. 35: ChangeInPgQlty vs ExASM with Weight = 0.7

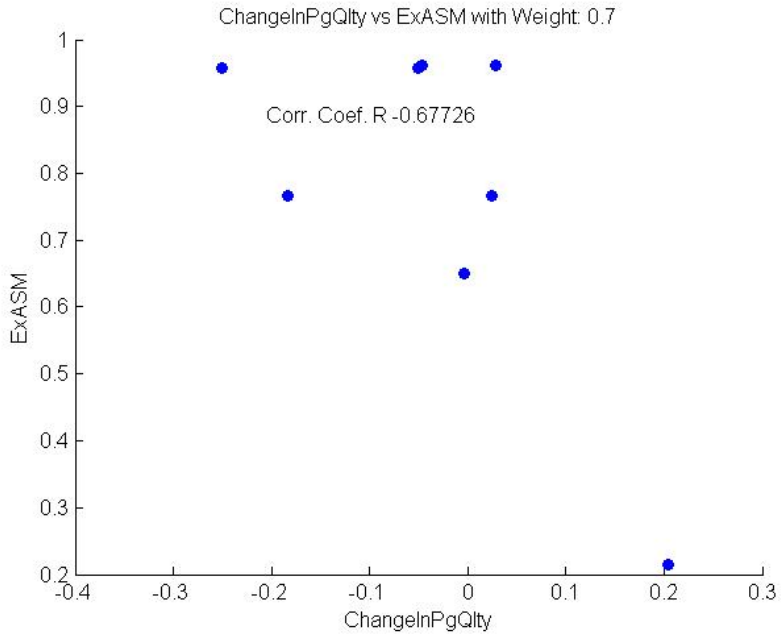


Fig. 36: ChangeInPgQlty vs ExASM with Weight = 0.8

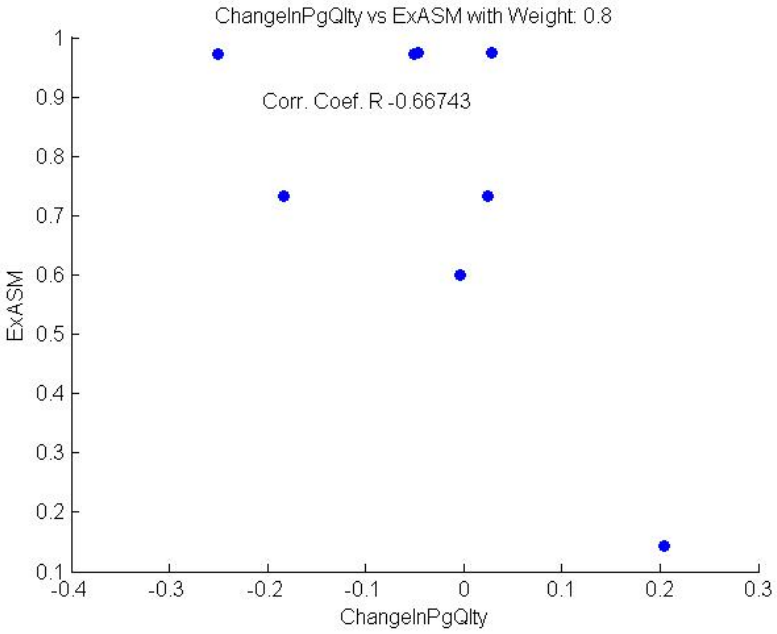


Fig. 37: ChangeInPgQlty vs ExASM with Weight = 0.9

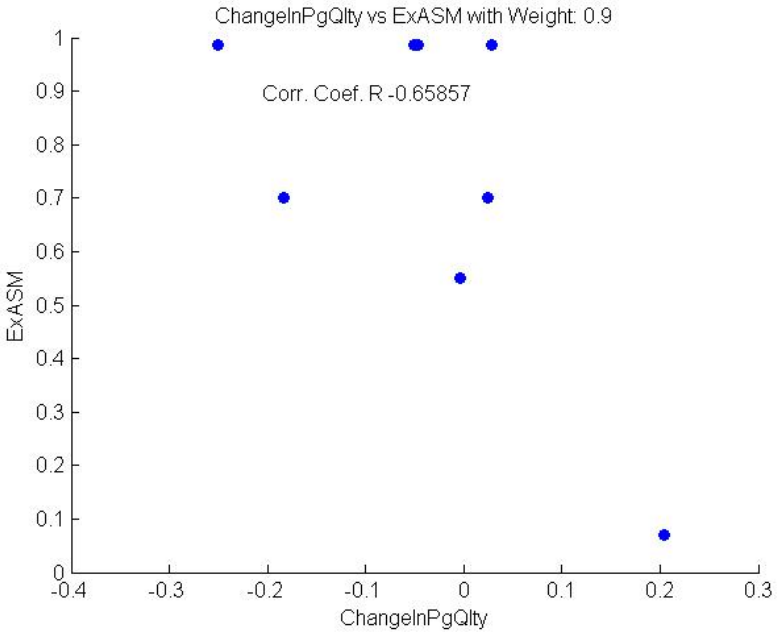


Fig. 38: ChangeInPgQlty vs ExASM with Weight = 1

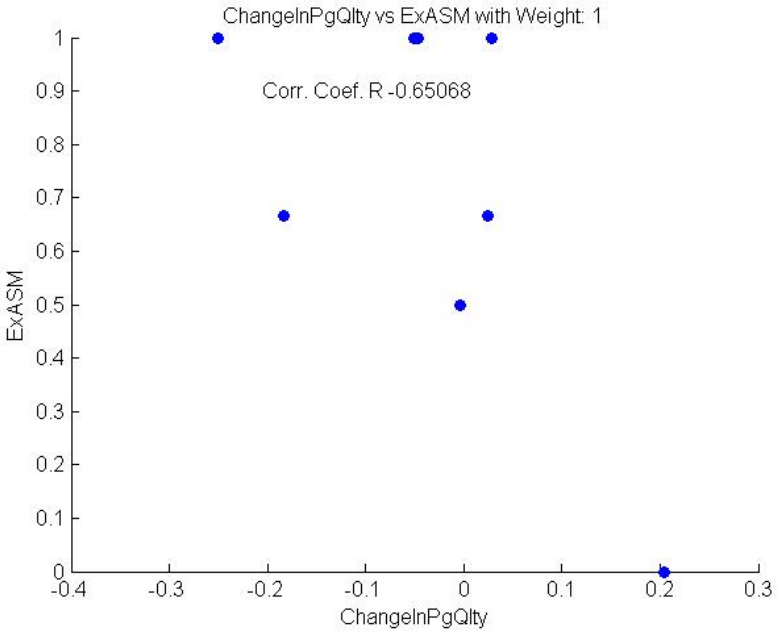


Table 13: Results summary for ExASM different weights

ExASM (W)	Corr Coef (R)
0	0.431177629104289
0.1	0.591184886009152
0.2	0.674356810255306
0.3	0.702755709790838
0.4	0.705299584271940

0.5	**0.698013363330291**
0.6	**0.687774150795452**
0.7	**0.677260259204672**
0.8	**0.667431428007379**
0.9	**0.658566084616091**
1	**0.650679543973478**

ExASM different weights

Table 13 shows relationship between ExASM (with w = 0.4) and ΔPackagingQlty metric for different cases of changes to subsequent versions

ExASM is the ExASM between initial and subsequent versions

ExASM with w = 0.4 gave the highest correlation coefficient R = 0.70530

A correlation of 0.7 was recorded when the ExASM weight is set to 0.4

because ExASM considers both inter-package and intra-package connections

ASM results summary

Table 14 shows relationship between ASM and PackagingQlty metric for different cases of changes to subsequent versions

The table shows cases of comparing earlier version with subsequent versions **with no packagingQlty optimization** to the subsequent versions after changes are applied

ASM is the ASM between initial and subsequent versions

Table 14: ASM results summary

Case No.	Initial version PgQlty	Subsequent version PgQlty	ΔPgQlty	ASM
2	0.71557	0.53254	0.18303	0.66667
3	0.71557	0.7439	0.02833	1
4	0.71557	0.71229	0.00328	0.5
5	0.71557	0.66557	0.05	1
6	0.71557	0.73938	0.02381	0.66667
7	0.71557	0.66937	0.0462	1
8	0.71557	0.91979	0.20422	0
9	0.71557	0.46542	0.25015	1

ExASM results summary

Table 15 shows relationship between ExASM (with w = 0.4) and ΔPackagingQlty (i.e. V2 – V1) metric for different cases of changes to subsequent versions

ExASM is the ExASM between initial and subsequent versions

ExASM with w = 0.4 gave the highest correlation coefficient R = 0.70530

Table 15: ExASM results summary

Case No.	Initial version PgQlty	Subsequent version PgQlty	ΔPgQlty	ExASM (w = 0.4)
2	0.71557	0.53254	-0.18303	0.86667
3	0.71557	0.7439	0.02833	0.92500
4	0.71557	0.71229	-0.00328	0.80000
5	0.71557	0.66557	-0.05	0.91429
6	0.71557	0.73938	0.02381	0.86667
7	0.71557	0.66937	-0.0462	0.92500
8	0.71557	0.91979	0.20422	0.42857
9	0.71557	0.46542	-0.25015	0.91429

ASM results summary optimal packages

This table shows relationship between ASM and PackagingQlty metric for different cases of changes to subsequent versions

The table shows cases of comparing earlier version with subsequent versions **with packagingQlty optimization** to the subsequent versions after changes are applied.

Table 16: ASM results summary optimal packages

Case No.	Initial version PgQlty	Subsequent version PgQlty	ΔPgQlty	ASM
2	0.71557	0.65405	0.06152	0
3	0.71557	0.7439	0.02833	1
4	0.71557	0.71229	0.00328	0.5
5	0.71557	0.66557	0.05	1
6	0.71557	0.73938	0.02381	0.66667
7	0.71557	0.73938	0.02381	0.66667
8	0.71557	0.91979	0.20422	0
9	0.71557	0.67488	0.04069	0

CEAM vs Packaging quality metric

CEAM four considered scenarios are:

Asterisk (*) represents case number 1 to 9

1. Scenario 1: CEAM vs PackagingQlty correlation check with V*.5
    a. V*.5 is obtained after making all case changes to V1.1

b. optimization is made to the resulting system

c. V*.5 is the best optimal system after changes

2. Scenario 2: CEAM vs PackagingQlty correlation check with V*.6

    a. V*.6 is obtained after making all case changes to V1.1

    b. optimization is made to the resulting system

    c. V*.6 is the second best optimal system after changes

3. Scenario 3: ChangeInCEAM vs ChangeInPackagingQlty correlation check with V1.2 and V*.2

    a. V1.2 is also the optimal configuration of the system

    b. That is V1.2 = V1.1

    c. V*.2 is obtained after making all case changes to V1.1

    d. optimization is made to the resulting system

    e. V*.2 is the best optimal system after changes

4. Scenario 4: ChangeInCEAM vs ChangeInPackagingQlty correlation check with V1.3 and V*.3

    a. V1.3 is second best optimal of V1.1

    b. V*.3 is obtained after making all case changes to V1.1

    c. Optimization is made to the resulting system

    d. V*.3 is the second best optimal system after changes

CEAM Results summary: Scenario 1

Table 17 shows case number that indicates hypothetical case version number, PgQlty gives the packaging quality value of the case version and CEAM gives the CEAM value of the case version. This was used to compute the correlation which can be visualized on Fig. 39. The correlation test score for this scenario is 0.41081. The p-value for this correlation test

is 0.2721 which is greater than significance level alpha which was set to value 0.05. This correlation test result is insignificant.

CEAM Results summary: Scenario 2

Table 18 shows case number that indicates hypothetical case version number, PgQlty gives the packaging quality value of the case version and CEAM gives the CEAM value of the case version. This was used to compute the correlation which can be visualized on Fig. 40. The correlation test score for this scenario is 0.48488. The p-value for this correlation test is 0.1859 which is greater than significance level alpha which was set to value 0.05. This correlation test result is insignificant.

CEAM Results summary: Scenario 3

Table 19 shows case number that indicates hypothetical case version number, Initial version PgQlty gives the packaging quality value of the initial case version. Subsequent version PgQlty gives the packaging quality value of the subsequent case version. ChangeInPgQlty gives the difference of packaging quality value of the initial case version from that of the subsequent case version. Initial version CEAM gives the CEAM value of the initial case version. Subsequent version CEAM gives the CEAM value of the subsequent case version. ChangeInCEAM gives the difference of CEAM value of the initial case version from that of the subsequent case version. The ChangeInPgQlty and ChangeInCEAM were used to compute the correlation which can be visualized on Fig. 41. The p-value for this correlation test is 0.0060 which is less than significance level alpha which was set to value 0.05.That is the correlation value is 95 percent significant.

CEAM Results summary: Scenario 4

Table 20 shows case number that indicates hypothetical case version number, Initial version PgQlty gives the packaging quality value of the initial case version. Subsequent version PgQlty gives the packaging quality value of the subsequent case version. ChangeInPgQlty gives the difference of packaging quality value of the initial case version from that of the subsequent case version. Initial version CEAM gives the CEAM value of the initial case version. Subsequent version CEAM gives the CEAM value of the subsequent case version. ChangeInCEAM gives the difference of CEAM value of the initial case version from that of the subsequent case version. The ChangeInPgQlty and ChangeInCEAM were used to compute the correlation which can be visualized on Fig. 42. The p-value for this correlation test is 1.5298e-05 which is less than significance level alpha which was set to value 0.05.That is the correlation value is 95 percent significant.

Table 17: PgQlty vs CEAM correlation scenario 1

Case No.	PgQlty	CEAM
1	0.71557	0.5
2	0.53254	0.416667
3	0.7439	0.5
4	0.71229	0.5
5	0.66557	0.5
6	0.73938	0.5
7	0.66937	0.5
8	0.91979	1
9	0.46542	0.611111

Fig. 39: PgQlty vs CEAM correlation scenario 1

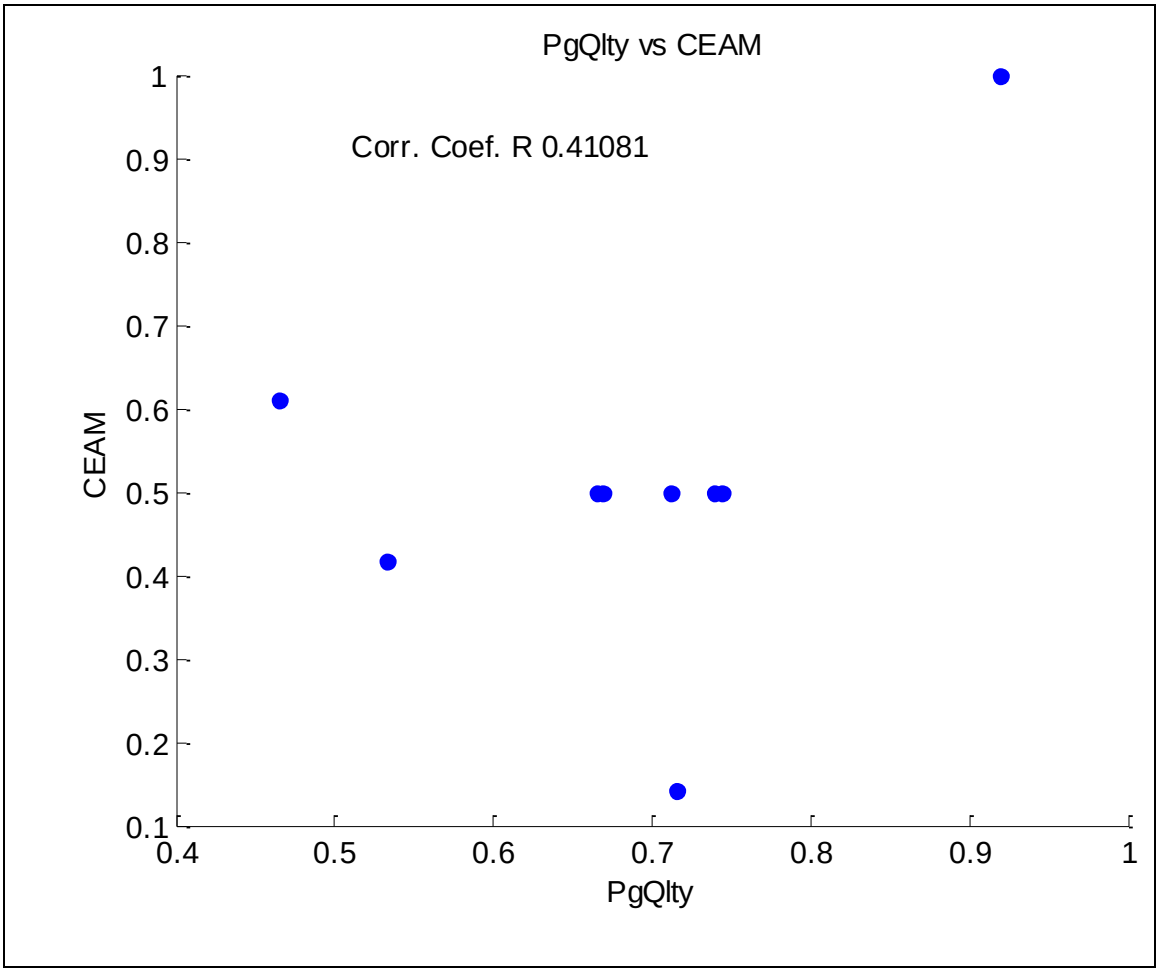


Table 18: PgQlty vs CEAM correlation scenario 2

Case No.	PgQlty	CEAM
1	0.71557	0.5
2	0.53254	0.555556
3	0.7439	0.555556
4	0.71229	0.611111
5	0.66557	0.5
6	0.73938	0.611111
7	0.66937	0.5
8	0.91979	1
9	0.46542	0.5

Fig. 40: PgQlty vs CEAM correlation scenario 2

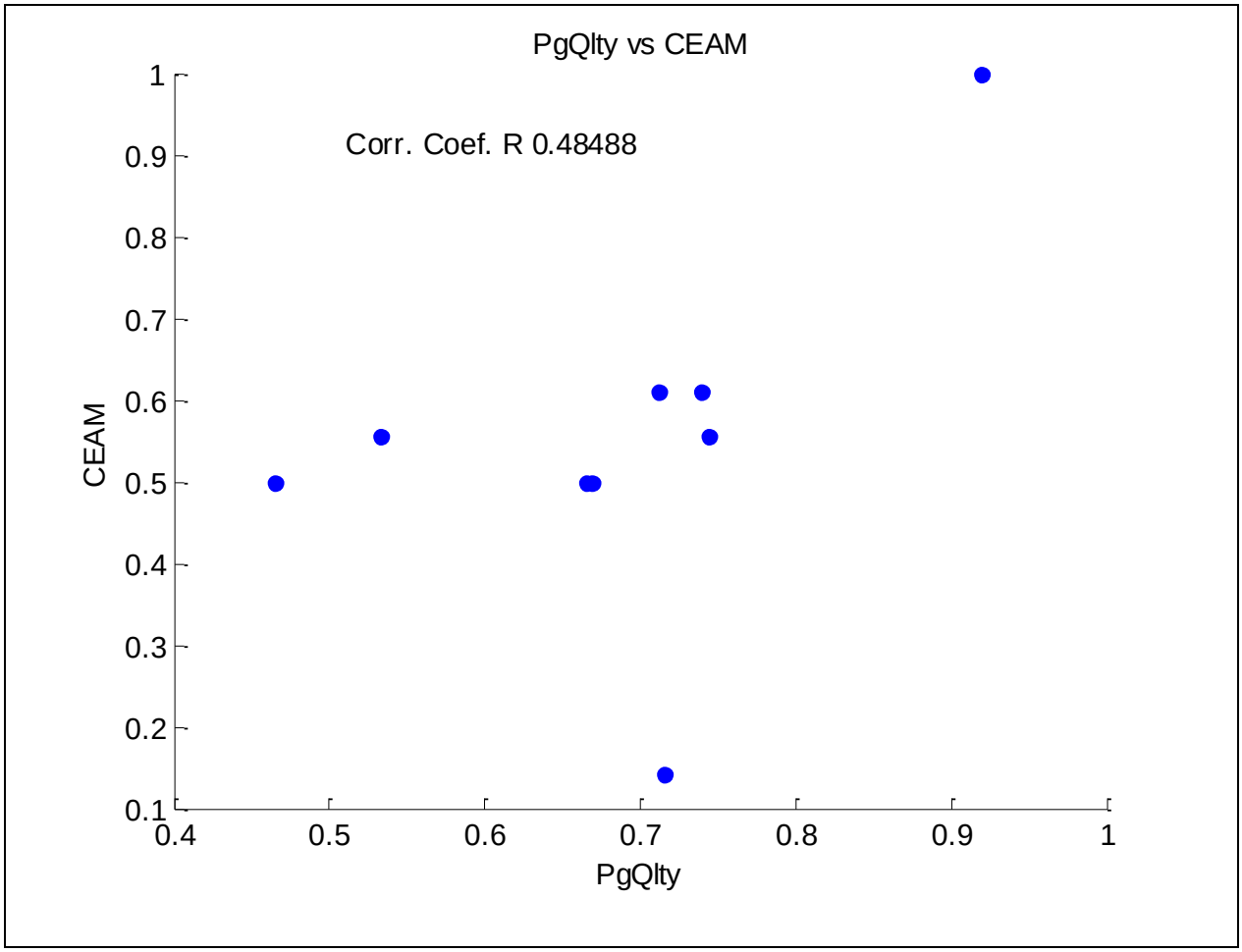


Table 19: ChangeInPgQlty vs ChangeInCEAM correlation scenario 3

Case No.	Initial version PgQlty	Subsequent version PgQlty	ΔPgQlty	Initial version CEAM	Subsequent version CEAM	ΔCEAM
2	0.71557	0.53254	-0.18303	0.5	0.416667	-0.08333
3	0.71557	0.7439	0.02833	0.5	0.5	0
4	0.71557	0.71229	-0.00328	0.5	0.5	0
5	0.71557	0.66557	-0.05	0.5	0.5	0
6	0.71557	0.73938	0.02381	0.5	0.5	0
7	0.71557	0.66937	-0.0462	0.5	0.5	0
8	0.71557	0.91979	0.20422	0.5	1	0.5
9	0.71557	0.46542	-0.25015	0.5	0.611111	0.111111

Fig. 41: ChangeInPgQlty vs ChangeInCEAM correlation scenario 3

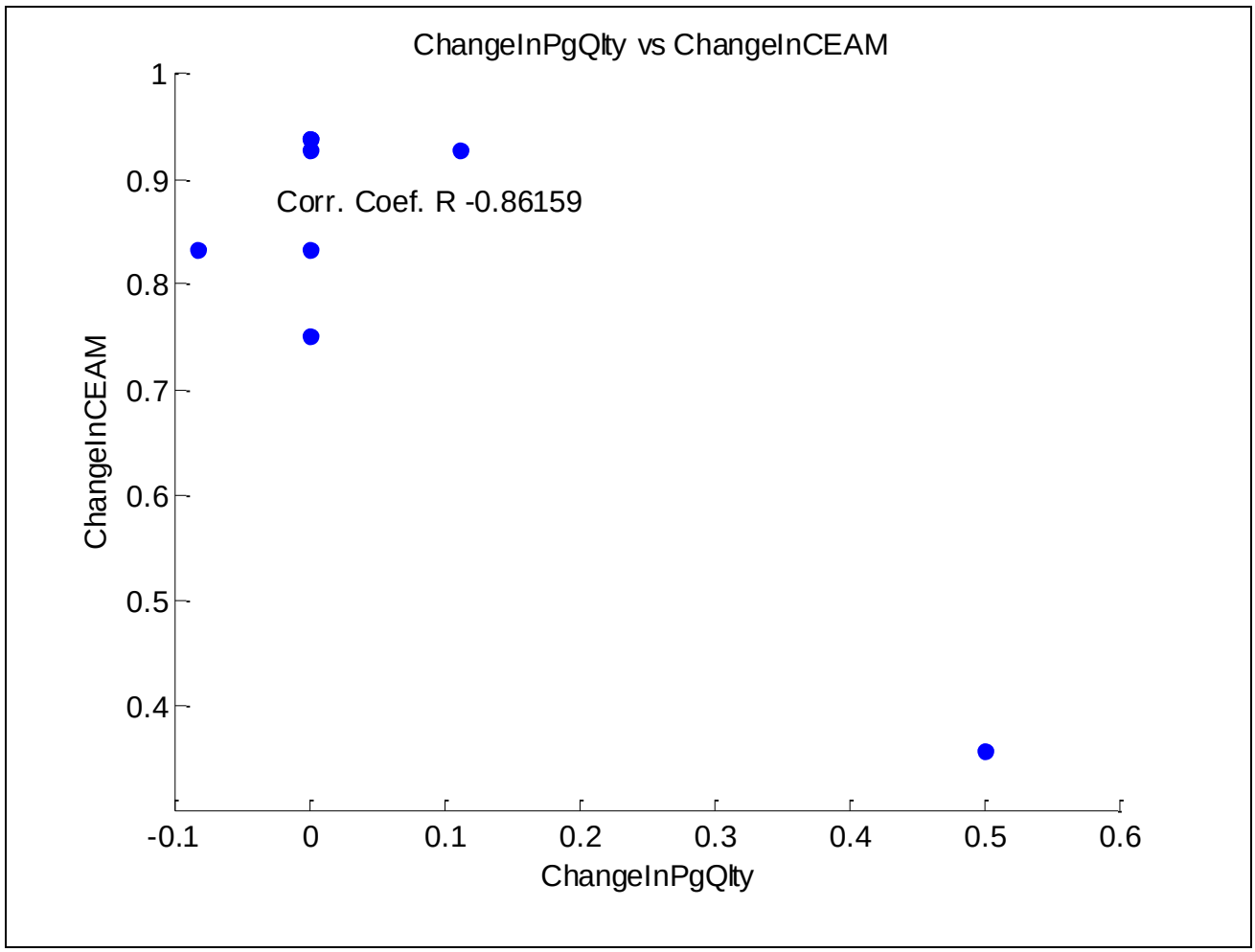
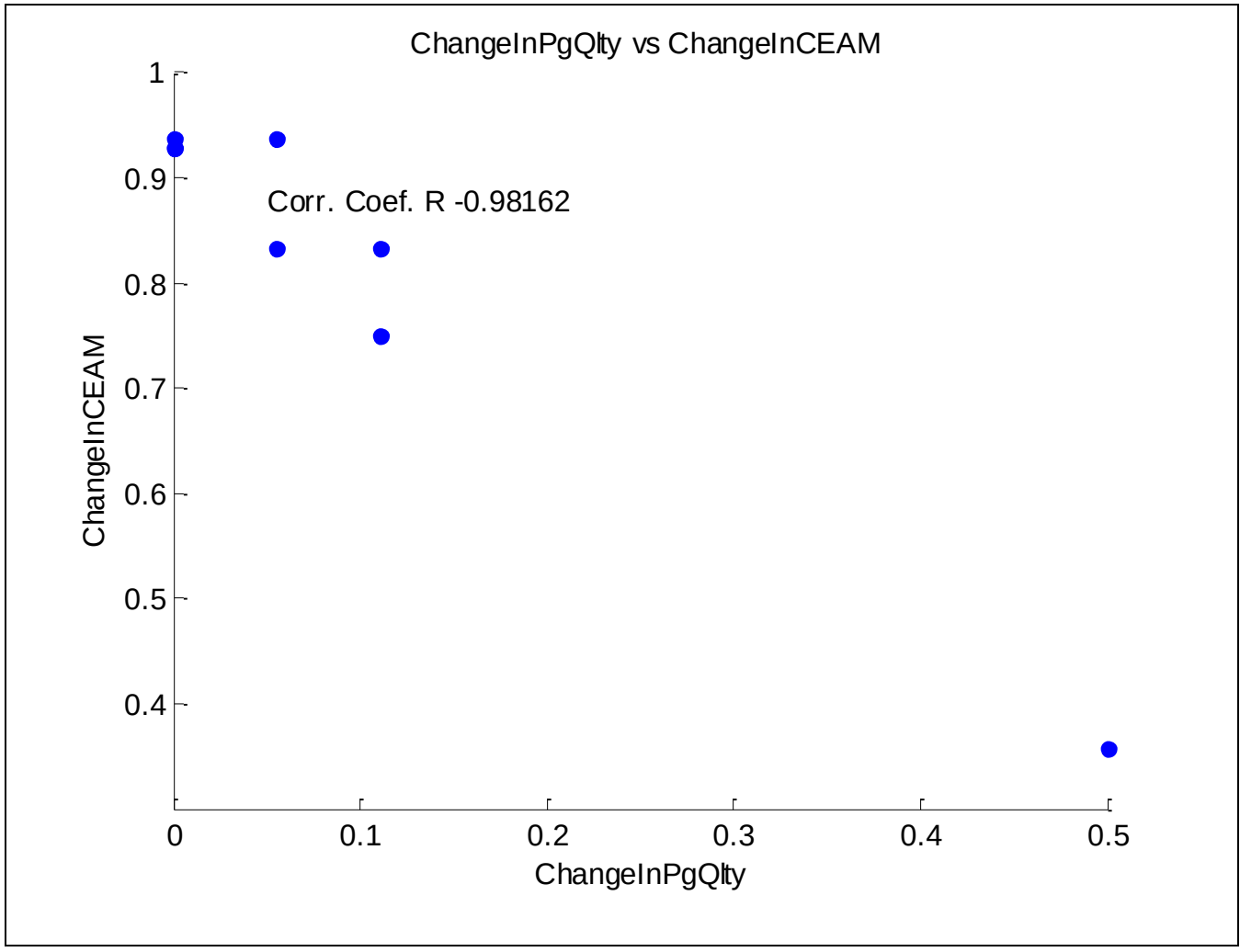


Table 20: ChangeInPgQlty vs ChangeInCEAM correlation scenario 4

Case No.	Initial version PgQlty	Subsequent version PgQlty	ΔPgQlty	Initial version CEAM	Subsequent version CEAM	ΔCEAM
2	0.71557	0.53254	-0.18303	0.5	0.555556	0.0556
3	0.71557	0.7439	0.02833	0.5	0.555556	0.0556
4	0.71557	0.71229	-0.00328	0.5	0.611111	0.1111

5	**0.71557**	**0.66557**	**-0.05**	**0.5**	**0.5**	**0**
6	**0.71557**	**0.73938**	**0.02381**	**0.5**	**0.611111**	**0.1111**
7	**0.71557**	**0.66937**	**-0.0462**	**0.5**	**0.5**	**0**
8	**0.71557**	**0.91979**	**0.20422**	**0.5**	**1**	**0.5000**
9	**0.71557**	**0.46542**	**-0.25015**	**0.5**	**0.5**	**0**

Fig. 42: ChangeInPgQlty vs ChangeInCEAM correlation scenario 4



Real case study

Two cases of real software were considered with 5 different values of w (0.2, 0.3, 0.4, 0.5, and 0.6).

- Case 1: ExASM of JHT 5.1 and JHT 5.2
- Case 1: ExASM of AWT 4 and JHT AWT 5

Table 21: ExASM real case study results summary (w = 0.2)

Case No.	Initial version PgQlty	Subsequent version PgQlty	ΔPgQlty	ExASM (w = 0.2)
1	0.17354	0.1789	0.00536	0.5671
2	0.37313	0.35078	-0.02235	0.3700

Table 22: : ExASM real case study results summary (w = 0.3)

Case No.	Initial version PgQlty	Subsequent version PgQlty	ΔPgQlty	ExASM (w = 0.3)
1	0.17354	0.1789	0.00536	0.5451
2	0.37313	0.35078	-0.02235	0.3414

Table 23: : ExASM real case study results summary (w = 0.4)

Case No.	Initial version PgQlty	Subsequent version PgQlty	ΔPgQlty	ExASM (w = 0.4)
1	0.17354	0.1789	0.00536	0.52307
2	0.37313	0.35078	-0.02235	0.3128

Table 24: : ExASM real case study results summary (w = 0.5)

Case No.	Initial version PgQlty	Subsequent version PgQlty	ΔPgQlty	ExASM (w = 0.5)
1	0.17354	0.1789	0.00536	0.5011
2	0.37313	0.35078	-0.02235	0.28415

Table 25: : ExASM real case study results summary (w = 0.6)

Case No.	Initial version PgQlty	Subsequent version PgQlty	ΔPgQlty	ExASM (w = 0.6)
1	0.17354	0.1789	0.00536	0.4791
2	0.37313	0.35078	-0.02235	0.2556

Discussion and conclusion: ASM ExASM, and CEAM

From how ASM works, there is no any correlation between it and the packagingQlty metric because ASM is purely based on inter-package connection (IPC. So if the is any changes that does not affect IPC then there won't be any changes to ASM. On the other hand if there are changes that affect the IPC then ASM is reduce. This is no matter the magnitude of changes as far as it does not affect ASM in a similar way then ASM will not change. ExASM with w = 0.4 gave the highest correlation coefficient R = 0.70530. For CEAM vs Packaging quality metric, a correlation of 0.9816 was recorded as the highest by scenario 4 with 95 percent significant.

Hypothesis 3: There is a correlation between the software packaging metric and the stability metric. This hypothesis can be accepted with the given statistics of CEAM by scenario 4.

The main challenge with the real case study is that it is still relatively expensive to compute the metric on it. So it takes a lot of time to run optimization algorithm to find optimal packaging configuration.

The expectation was that given a software with an initial version v1 packaged with a certain configuration C1 and after evolution into a new version V2 with configuration C2. If the difference between the 2 versions packagingQlty is low then ExASM between them should be high. On the other hand if the difference between the packagingQlty of both version is high, then the ExASM between them was expected to be low. However the result did not turn out to support that rational.

PackagingQlty also considers intra-package and inter-package connection among several many factors as enumerated earlier. However, ExASM is based on just intra-package and inter-package connections.

Moreover we can look at the investigation in the other way where the packaging metric actually validates the ExASM metric. That is the ExASM which is based on just changes intra-package and inter-package connections, may not actually be able to capture the stronger concept of architectural stability.

Software packaging quality metric from its conception and rational is actually meant to embody the qualities of software architectural stability metric. Moreover it considers many other factors that affects software architectural stability. Thus software packaging quality

can be seen also as quantification of software stability. Along this line of thought, it will be easy to see why the ExASM will be inadequate to quantify software stability.

4.4 Optimization algorithms experiment

The solution representation preliminary experiment enable us to get idea of values of common parameters among the optimization algorithms. It will also let us make a fair and balanced comparison. Moreover we also take note of algorithm parameters that will not affect the desired output so that they can be fixed. This will also help rapidly scale down the number of experiments. The penalized model was used with the model parameters fixed to what was learned at the model selection experiment stage in section 4.3 Search grid technique is used to find the parameter values for each algorithm that gives the best output value. The experiment design earlier was used for this experiment also to further systematically scale down the number of experiments. The only output measure used to compare the algorithms of output measures used to evaluate the algorithms

4.4.1 Result optimization algorithms evaluation

The result of experiment of comparing 3 algorithms (GA, CMA-ES, and DE) on the hypothetical case study is reported below. For each algorithm, a table comprising of algorithm parameters, instance number (that is a given combination of parameters), average score from three runs of an instance, and the best score from that instance. The graphical plot display that shows the performance of the algorithms is captured at the end of the optimization and depicted below to give a visualization of the performance of each algorithm. How the graphical plot is interpreted is explained in section 2.2.6.Among all the algorithms being reported CMA-ES performed better since it has the lowest average scores.

The detailed table of result of GA experiment can be found on Appendix 2. Table 26 shows the GA parameter values that were tested. Table 27 gives summary of result of the GA parameter search experiment.

Table 26: GA parameters setting

	GA parameters			
mutation	1	2	3	4
	Mutate Adaptive feasible	Mymutate = 0.2	Mymutate = 0.5	Mymutate = 0.8
crossover	1	2	3	4
	crxscatter	crxrlfipr	Crxrandperm: noperm = noclass	Crxrandperm: noperm = 2*noclass
creation	1	2	3	
	Create: mean = 0.2 Create: sdv = 0.07	Create: mean = 0.2 Create: sdv = 0.1	Create: mean = 0.2 Create: sdv = 0.3	
	4	5	6	
	Create: mean = 0.5 Create: sdv = 0.07	Create: mean = 0.5 Create: sdv = 0.1	Create: mean = 0.5 Create: sdv = 0.3	
	7	8	9	
	Create: mean = 0.7 Create: sdv = 0.07	Create: mean = 0.7 Create: sdv = 0.1	Create: mean = 0.7 Create: sdv = 0.3	

Table 27: GA experiment result summary

	mutation	crossover	creation	score	configuration						
Best GA	3	3	4	-0.7156	1	1	1	1	1	2	2
	3	4	5	-0.7156	1	1	1	1	1	2	2
Mean	-0.6463										
Std dev	0.0886										

The detailed table of result of DE experiment can be found on Appendix 2. Table 28 shows the DE parameter values that were tested. Table 29 gives summary of result of the DE parameter search experiment.

Table 28: DE parameters

	DE parameters		
Mutation scale	1	2	3
	0.2	0.5	0.8
Crossover rate	1	2	3
	0.5	0.7	0.9
creation	1	2	3
	Create: mean = 0.2 Create: sdv = 0.07	Create: mean = 0.2 Create: sdv = 0.1	Create: mean = 0.2 Create: sdv = 0.3
	4	5	6
	Create: mean = 0.5 Create: sdv = 0.07	Create: mean = 0.5 Create: sdv = 0.1	Create: mean = 0.5 Create: sdv = 0.3
	7	8	9
	Create: mean = 0.7 Create: sdv = 0.07	Create: mean = 0.7 Create: sdv = 0.1	Create: mean = 0.7 Create: sdv = 0.3

Table 29: DE experiment result summary

Best DE	mutation	crossover	creation	score			configu
	2	1, 2 and 3	4 and 5	-0.7156	1	1	1
Mean	-0.6511						
Std dev	0.0883						

The detailed table of result of CMAES experiment can be found on Table 32. Table 30 shows the DE parameter values that were tested. Table 31 gives summary of result of the DE parameter search experiment.

Table 30: CMAES parameters setting

	CMAES parameters		
Creation	1	2	3
	Create: mean = 0.2 Create: sdv = 0.07	Create: mean = 0.2 Create: sdv = 0.1	Create: mean = 0.2 Create: sdv = 0.3
	4	5	6
	Create: mean = 0.5 Create: sdv = 0.07	Create: mean = 0.5 Create: sdv = 0.1	Create: mean = 0.5 Create: sdv = 0.3
	7	8	9
	Create: mean = 0.7 Create: sdv = 0.07	Create: mean = 0.7 Create: sdv = 0.1	Create: mean = 0.7 Create: sdv = 0.3

Table 31: CMAES experiment result summary

Best DE	creation	score	configuration						
	all	-0.7156	1	1	1	1	1	2	2
Mean		-0.7156							
Std dev		0							

Table 32: CMAES experiment result

creation	average	best configuration of 5 trial runs						
1	-0.7156	1	1	1	1	1	2	2
2	-0.7156	1	1	1	1	1	3	3
3	-0.7156	1	1	1	1	1	2	2
4	-0.7156	1	1	1	1	1	2	2
5	-0.7156	1	1	1	1	1	3	3
6	-0.7156	1	1	1	1	1	3	3
7	-0.7156	1	1	1	1	1	3	3
8	-0.7156	2	2	2	2	2	1	1
9	-0.7156	1	1	1	1	1	2	2

CHAPTER 5

CONCLUSION

5.1 Contributions and their implications

Steps to be taken to identify, analyze, formulate and solve an optimization (multi or single objective) problem were clearly outlined. This will serve as a contribution guide for researcher pursuing this endeavor.

Ways in which an objective function can be formulated were clearly shown. It was shown clearly the relationship between machine learning and optimization. This will provide help for new and novice researchers to understand what they mean and how they relate.

A neural network interpretation of the original model was done successfully and the metric extended thereby. Thus, a path for feature research in automation of quantification and qualification of software artifacts is shown. This will pave way for applying and investigating several neural network techniques for packaging software systems.

This way, simple metrics can be acquired to formulate different architecture of neural networks then train them by using a training and validation dataset.

Consequently, neural network technique can be applied to other software engineering by acquiring simple software metrics from good knowledge of metrics formulation or simply by use of metric tools one can be able to develop a model for automatic quantification or qualification of software artifacts.

This study helps to further strengthen and demonstrate the justification and popularity of neural networks as current state-of-the-art in modeling. We can see that though the original model was formulated by the designer by handwork and hard work - reasoning through how simple metrics should be combined to formulate higher level metrics in layer wise hierarchical manner, and subsequently the desired output was reached. However, the same desired output (and even better) can be reached by application of neural network techniques without the hassle of going through manually formulating complicated but necessary feature need to reach the desired output.

So the lesson is, we should not spend effort formulating latent features that are complicated (and even incomprehensible that we even run out of how to name them) instead acquire as many of the direct features as possible and let the neural network learn the higher level features by itself.

5.2 Threats to validity

5.2.1 Threats to construct validity

To be sure we actually measured what we conceive as software packaging quality, software projects that have lived long over several evolutions have to be documented.

The notion of architectural stability is a very strong qualitative and abstract concept. One can debate if the metrics ASM and ExASM are actually able to capture that strong concept. Because ASM and ExASM where defined based on the assumption that change is reverse of stability. Stability may entail more than just that.

Question may be raised as regard whether metric can actually be referred to as convolutional neural network (CNN). However, with all conviction and from earlier authoritative works we can truly refer to the metric as a CNN.

5.2.2 Threats to external validity

The case studies considered will still be considered inadequate to make a true generalization about the research objective. More studies have to be done with more real cases to have more statistical significance and to enable more confident conclusion.

5.2.3 Threats to Internal validity

The much training and validation data is usually needed to train and validate neural network. In this experiment hypothetical case study data and expert suggested configuration ranking was used as in training and validation of the neural network. This may be very difficult in real case.

5.3 Future work

Meta-optimization for tuning model and hyper parameters. We could study how effective meta-optimization could be for this kind of optimization problem. Afterwards, we could also study how well some optimization algorithm do when used for meta-optimization.

Investigate other outputs attributes of meta-heuristic algorithms and how the correlate with solutions, the algorithms' parameters and each other. In this case it is a Multi-objective Meta-optimization of OA.

A more succinct neural network interpretation of the original overallpackaing metric.

Creating training and validation dataset using the hypothetical case study configurations and Spearman rank correlation coefficient ranking as fitness function.

Investigate how the metrics used can be mined from source code and runtime logs. In this work the metrics are formulated from UCs. Perhaps, there may be already existing source code and runtime metrics that are correlated with the metrics used in this work.

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Appendix 1: ASM, ExASM, CEAM Cases Illustration

Table 33 illustrates the first of nine case of modification to the hypothetical case study as discussed in Section 0. In this case Packaging configuration of V1.1 remains same as [ABCDE, FG]

Table 33: Case 1: ASM, ExASM, CEAM of v1.1 and v1.1

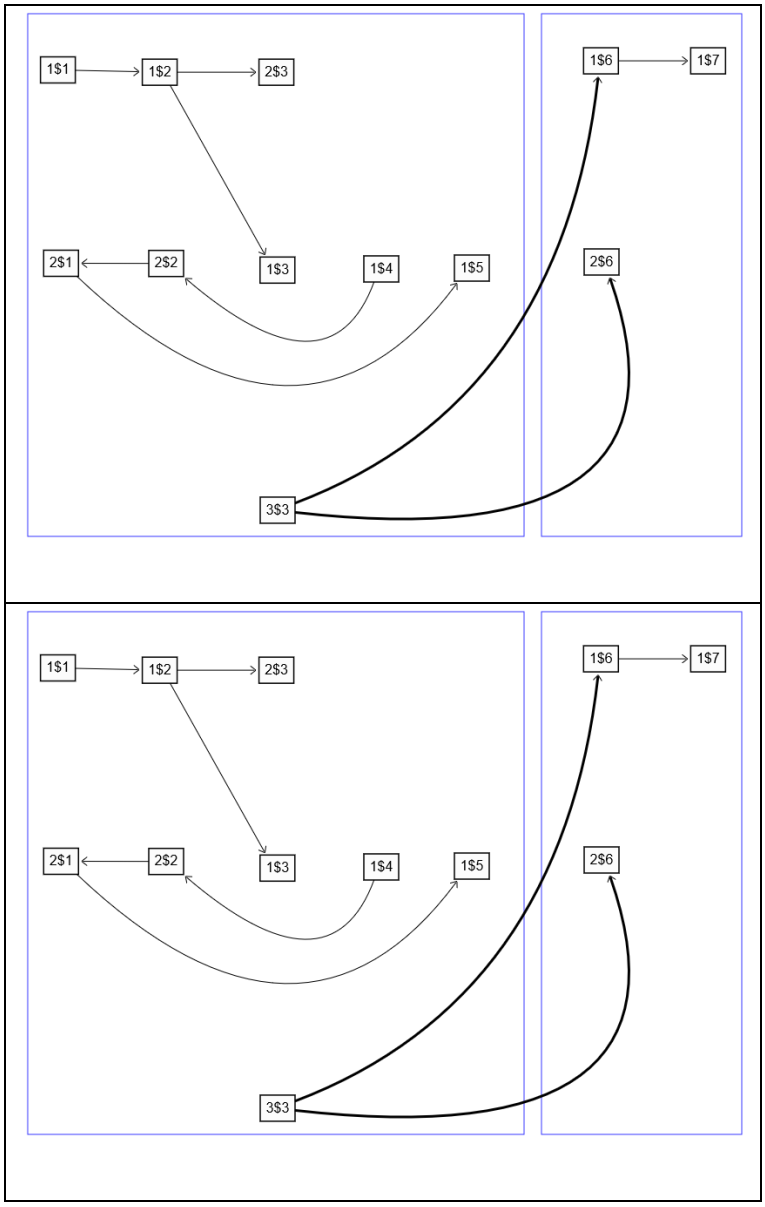

Table 34 illustrates the second of nine case of modification to the hypothetical case study as discussed in Section 0. In this case Packaging configuration of V2.1 remains same as that of V1.1 as [ABCDE, FG]

Table 34: Case 2: adding an inter-package call into V1.1 to make V2.1

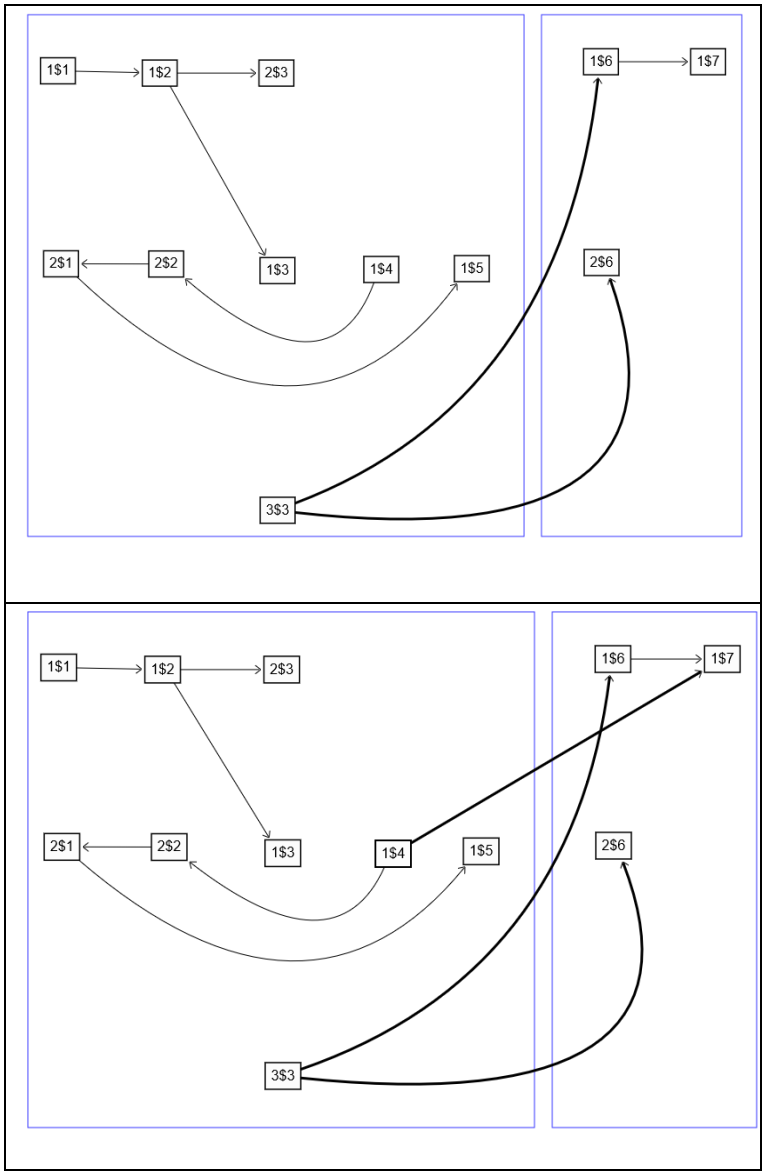

Table 35 illustrates the third of nine case of modification to the hypothetical case study as discussed in Section 0. In this case Packaging configuration configuration of V3.1 remains same as V1.1 as [ABCDE, FG]

Table 35: Case 3: adding an intra-package call into V1.1 to make V3.1

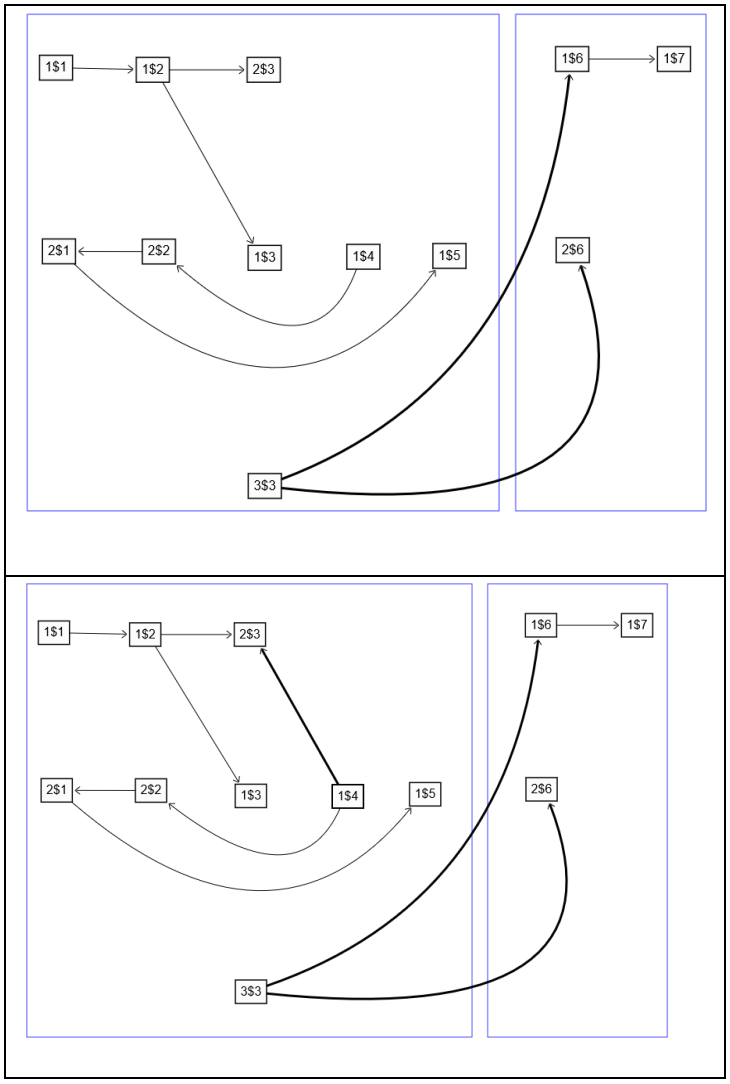

Table 36 illustrates the fourth of nine case of modification to the hypothetical case study as discussed in Section 0. In this case Packaging configuration of V4.1 remains same as V1.1 as [ABCDE, FG]

Table 36: Case 4: deleting an inter-package call from V1.1 to make V4.1

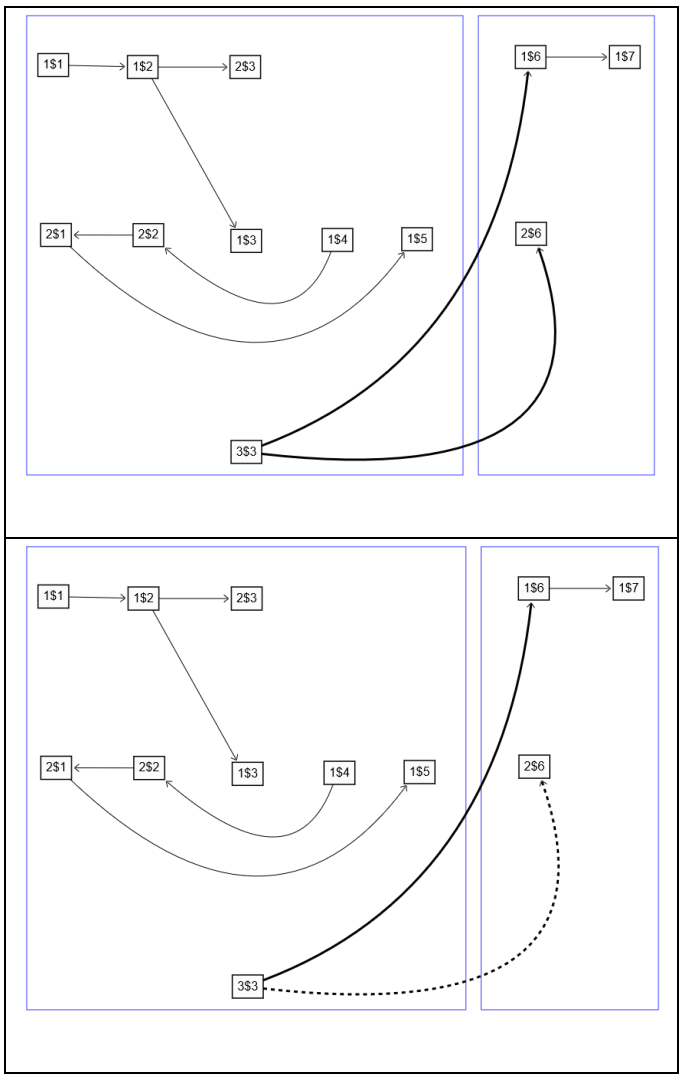

Table 37 illustrates the fifth of nine case of modification to the hypothetical case study as discussed in Section 0. In this case Packaging configuration of V5.1 remains same as V1.1 as [ABCDE, FG]

Table 37: Case 5: deleting an intra-package call from V1.1 to make V5.1

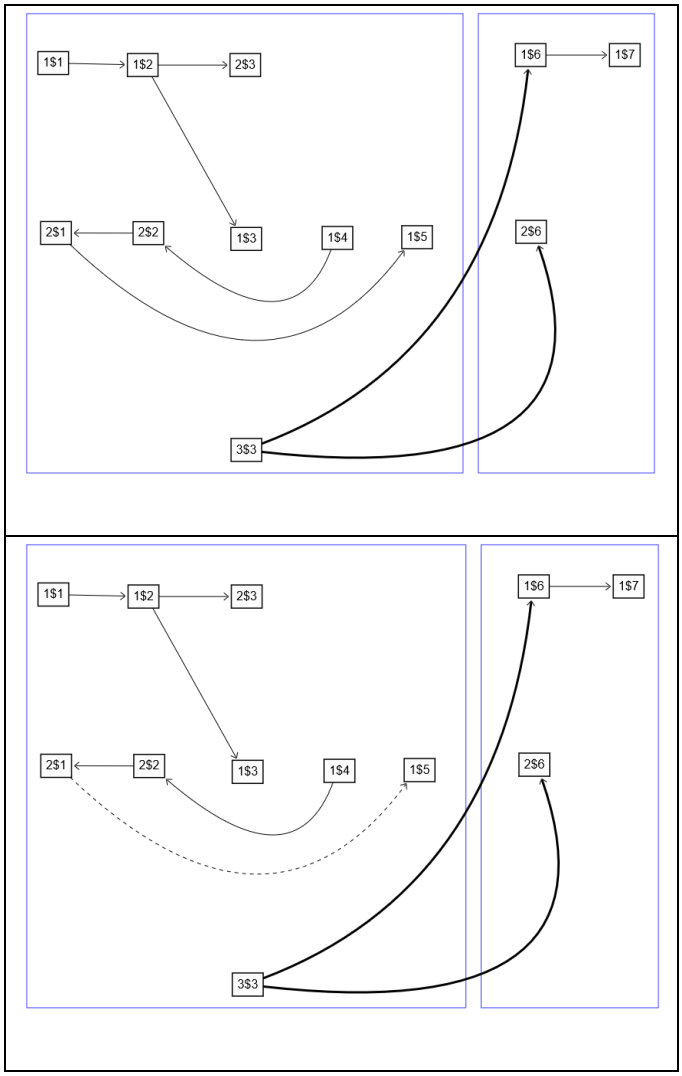

Table 38 illustrates the sixth of nine case of modification to the hypothetical case study as discussed in Section 0. In this case Packaging configuration of V6.1 is [ABCDE, FGH]

Table 38: Case 6: adding a class making inter-package call into V1.1 to makeV6.1

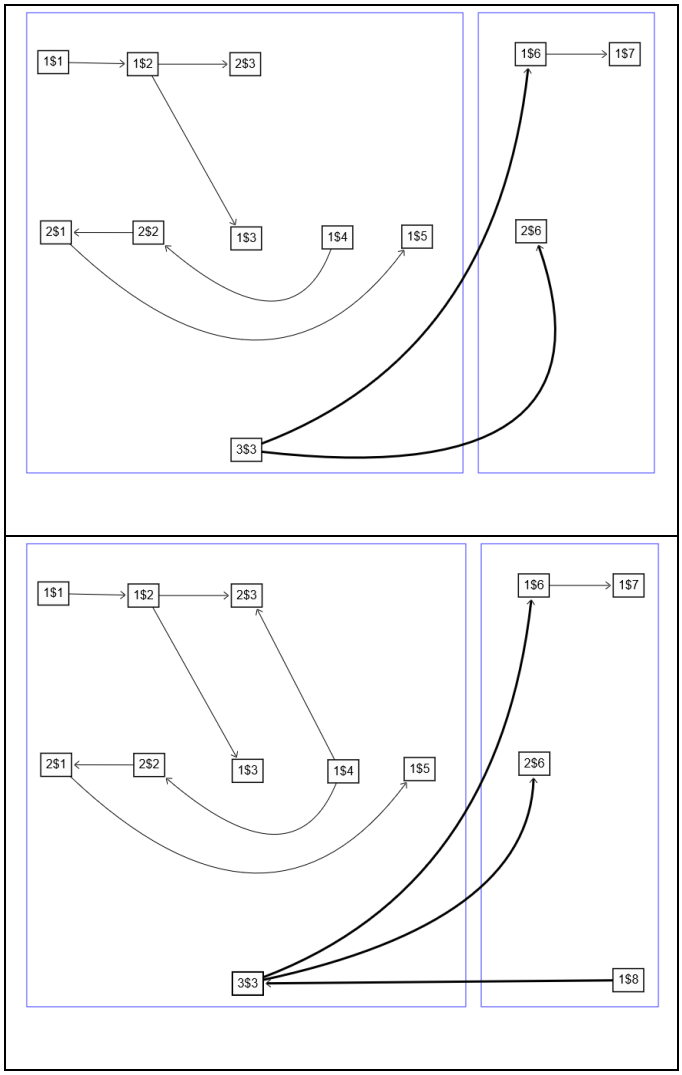

Table 39 illustrates the seventh of nine case of modification to the hypothetical case study as discussed in Section 0. In this case Packaging configuration of V7.1 is [ABCDEH, FG]

Table 39: Case 7: adding a class making intra-package call into V1.1 to make V7.1

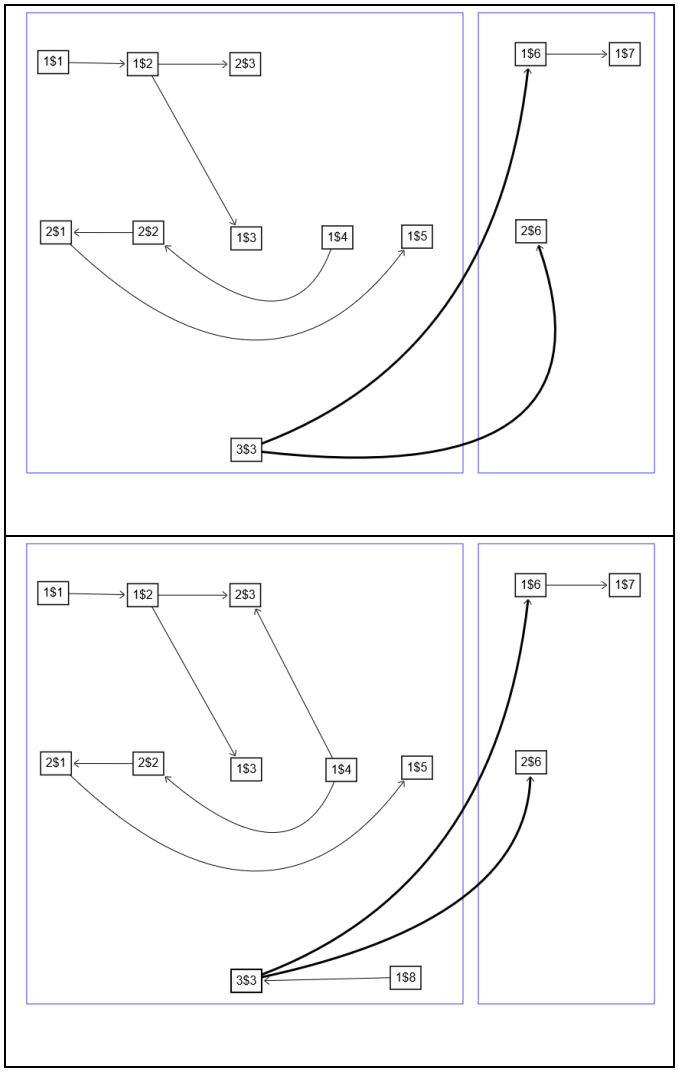

Table 40Table 33 illustrates the eighth of nine case of modification to the hypothetical case study as discussed in Section 0. In this case Packaging configuration of V8.1 same as [ABDE, FG]

Table 40: Case 8: deleting a class making inter-package call from V1.1 to makeV8.1

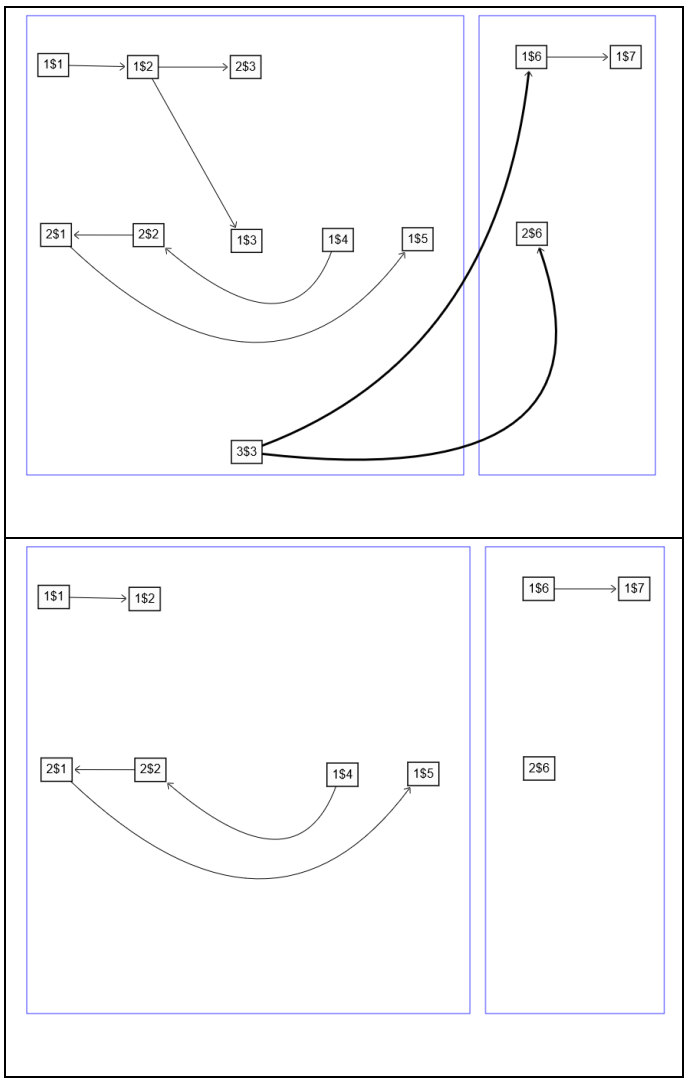

Table 41 illustrates the ninth of nine case of modification to the hypothetical case study as discussed in Section 0. In this case Packaging configuration of V9.1 same as

[ABCDE, F]

Table 41: Case 9: deleting a class making intra-package call from V1.1 to makeV9.1

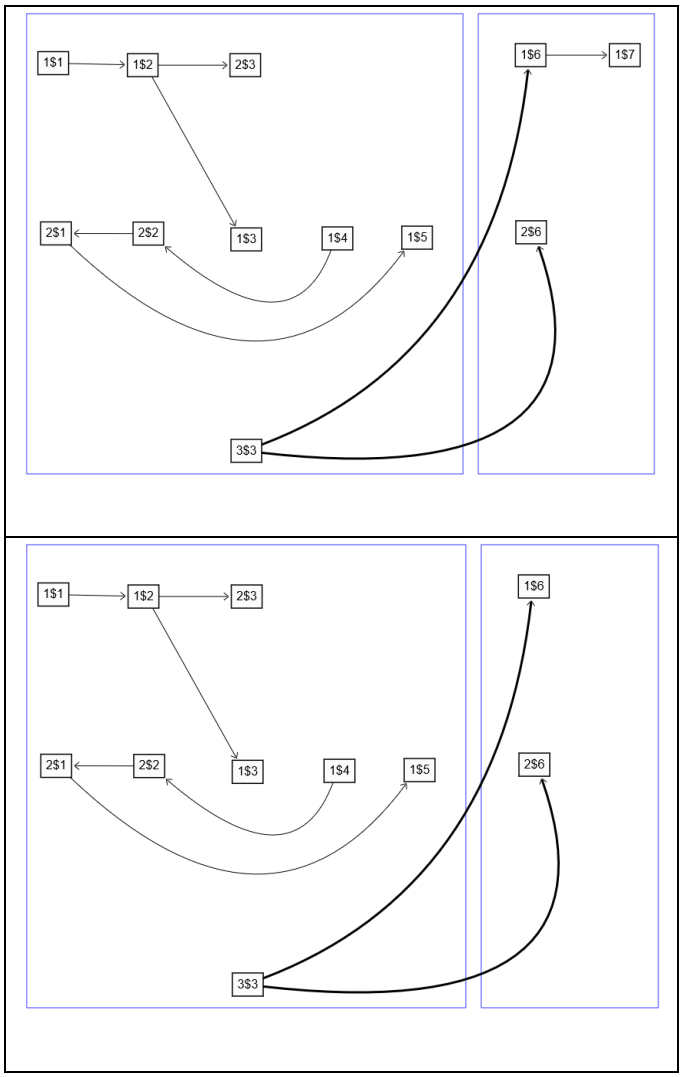

Table 42 shows just a test run of the ASM calculator system. ASM (V1.1, V1.1). ASM is calculated based on inter-package call (inter-PC). This program was developed for this thesis work.

Table 42: Case 1: ASM of v1.1 and v1.1

```
==============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.12057
Number of packages: 2

_____________________________
Individual score: 0.71557
Individual score type: Ebad
==============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 1
=============
```

Table 43 shows just a test run of the ExASM calculator system. ExASM(V1.1, V1.1, 0.4). ExASM is based on both Intra-package connection and Inter-package connection. This program was developed for this thesis work.

Table 43: Case 1: ExASM of v1.1 and v1.1

```
============================
Individual ID: 1&1&2&1&1&2&2
compute time: 0.041294
Number of packages: 2

_____________________________
Individual score: 0.70156
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  3    3   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  4    4   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  5    5   3$3-1$6        [2 2]      [3 6]    3$3    1$6
  6    6   1$6-1$7        [2 2]      [6 7]    1$6    1$7
  7    7   3$3-2$6        [2 2]      [3 6]    3$3    2$6


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$2-1$3        [1 2]      [2 3]    1$2    1$3
  2    2   1$2-2$3        [1 2]      [2 3]    1$2    2$3


======================


=================
ExASM(w = 0.4): 1
=================
```

Table 44 shows ASM program output for ASM(V1.1, 2.1).

Table 44: Case 2: ASM adding an inter-package call into V1.1 to make V2.1

```
============================
Individual ID: 1&1&1&1&2&2
compute time: 0.11959
Number of packages: 2

_____________________
Individual score: 0.53254
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
-------------------------------------------------------
  1    1   1$1-1$2       [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3       [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3       [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2       [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1       [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5       [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7       [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
-------------------------------------------------------
  1    1   1$4-1$7       [1 2]      [4 7]    1$4    1$7
  2    2   3$3-1$6       [1 2]      [3 6]    3$3    1$6
  3    3   3$3-2$6       [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 0.55556
=============
```

Table 45 shows ExASM program output for ExASM (V1.1, 2.1, 0.4)

Table 45: Case 2: ExASM adding an inter-package call into V1.1 to make V2.1

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.0596
Number of packages: 2

_________________________
Individual score: 0.53254
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$4-1$7        [1 2]      [4 7]    1$4    1$7
  2    2   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  3    3   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=================
ExASM(w = 0.4): 0.86667
=================
```

Table 46 and Table 47 shows Case 2: Top 2 configurations of V1.1 and V2.1 after optimization search as (V1.2, V1.3) and (V2.2, V2.3). Note V1.2 = V1.1 since V1.1 is the top most configuration [1 1 1 1 1 2 2] ([ABCDE, FG]). V1.3 is [1 1 2 1 1 2 2] ([ABDE, CFG]). V2.2 is supposed to be [1 1 1 1 1 1 1] ([ABCDEFG]) with Ebad score 0.73016. But this is not a desired configuration. So the next top is taken as V2.2 with [1 1 1 2 2 1 1] ([ABCFG, DE]) with score 0.65405. V2.3 is [1 1 2 3 3 2 2] ([AB, CFG, DE]) with Ebad score 0.6195

Table 46: Case 2: Top 2 configurations of V1.1 and V2.1 after optimization search as (V1.2, V1.3)

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.12057
Number of packages: 2

_____________________
Individual score: 0.71557
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 1
=============
```

```
============================
Individual ID: 1&1&1&2&2&1&1
compute time: 0.12853
Number of packages: 2

_____________________
Individual score: 0.65405
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [3 3]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [3 3]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [3 3]      [2 3]    1$2    2$3
  4    4   2$2-2$1        [3 3]      [2 1]    2$2    2$1
  5    5   3$3-1$6        [3 3]      [3 6]    3$3    1$6
  6    6   1$6-1$7        [3 3]      [6 7]    1$6    1$7
  7    7   3$3-2$6        [3 3]      [3 6]    3$3    2$6


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$4-2$2        [5 3]      [4 2]    1$4    2$2
  2    2   2$1-1$5        [3 5]      [1 5]    2$1    1$5
  3    3   1$4-1$7        [5 3]      [4 7]    1$4    1$7


======================


=============
ASM: 0.55556
=============
```

Table 47: Case 2: Top 2 configurations of V1.1 and V2.1 after optimization search as (V2.2, V2.3)

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.12057
Number of packages: 2

Individual score: 0.71557
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
-------------------------------------------------------
  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
-------------------------------------------------------
  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 1
=============
```

```
============================
Individual ID: 1&1&2&3&3&2&2
compute time: 0.10546
Number of packages: 3

Individual score: 0.6195
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
-------------------------------------------------------
  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  3    3   3$3-1$6        [2 2]      [3 6]    3$3    1$6
  4    4   1$6-1$7        [2 2]      [6 7]    1$6    1$7
  5    5   3$3-2$6        [2 2]      [3 6]    3$3    2$6


interpc
  #   id      pcid   packageids   classids   fun1   fun2
-------------------------------------------------------
  1    1   1$2-1$3        [1 2]      [2 3]    1$2    1$3
  2    2   1$2-2$3        [1 2]      [2 3]    1$2    2$3
  3    3   1$4-2$2        [3 1]      [4 2]    1$4    2$2
  4    4   2$1-1$5        [1 3]      [1 5]    2$1    1$5
  5    5   1$4-1$7        [3 2]      [4 7]    1$4    1$7


======================


=============
ASM: 1
=============
```

Table 48 shows ASM program output for ASM (V1.1, 3.1)

Table 48: Case 3: ASM adding an additional intra-package call into V1.1 to make V3.1

```
============================
Individual ID: 1&1&1&1&2&2
compute time: 0.10554
Number of packages: 2

____________________________
Individual score: 0.7439
Individual score type: Ebad
============================
intrapc
  #   id      pcid    packageids    classids    fun1    fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]       [1 2]    1$1     1$2
  2    2   1$2-1$3        [1 1]       [2 3]    1$2     1$3
  3    3   1$2-2$3        [1 1]       [2 3]    1$2     2$3
  4    4   1$4-2$2        [1 1]       [4 2]    1$4     2$2
  5    5   2$2-2$1        [1 1]       [2 1]    2$2     2$1
  6    6   2$1-1$5        [1 1]       [1 5]    2$1     1$5
  7    7   1$4-2$3        [1 1]       [4 3]    1$4     2$3
  8    8   1$6-1$7        [2 2]       [6 7]    1$6     1$7


interpc
  #   id      pcid    packageids    classids    fun1    fun2
_____________________________________________________________

  1    1   3$3-1$6        [1 2]       [3 6]    3$3     1$6
  2    2   3$3-2$6        [1 2]       [3 6]    3$3     2$6


======================


=============
ASM: 1
=============
```

Table 49 shows ExASM program output for ExASM (V1.1, V3.1, 0.4)

Table 49: Case 3: ExASM adding an additional intra-package call into V1.1 to make V3.1

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.050639
Number of packages: 2

_________________________
Individual score: 0.7439
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$4-2$3        [1 1]      [4 3]    1$4    2$3
  8    8   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=================
ExASM(w = 0.4): 0.925
=================
```

Table 50 and Table 51 shows Case 3: Top 2 configurations of V1.1 and V3.1 after optimization search as (V1.2, V1.3) and (V3.2, V3.3). Note V1.2 = V1.1 since V1.1 is the top most configuration [1 1 1 1 1 2 2] ([ABCDE, FG]). V1.3 is [1 1 2 1 1 2 2] ([ABDE, CFG]). V3.2 is [1 1 1 1 1 2 2] ([ABCDE, FG]) with score 0.7439. V3.3 is supposed to be [1 1 1 1 1 1 1] ([ABCDEFG]) with Ebad score 0.73016. But this is not a desired configuration. So the next top is taken as V3.3 with [1 1 1 2 2 3 3] ([ABC, DE, FG]) with Ebad score 0.71243.

Table 50: Case 3: Top 2 configurations of V1.1 and V3.1 after optimization search as (V1.2, V1.3)

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.12057
Number of packages: 2

_____________________________
Individual score: 0.71557
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]   1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]   1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]   1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]   1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]   2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]   2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]   1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]   3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]   3$3    2$6


======================


=============
ASM: 1
=============
```

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.11948
Number of packages: 2

_____________________________
Individual score: 0.7439
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]   1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]   1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]   1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]   1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]   2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]   2$1    1$5
  7    7   1$4-2$3        [1 1]      [4 3]   1$4    2$3
  8    8   1$6-1$7        [2 2]      [6 7]   1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]   3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]   3$3    2$6


======================


=============
ASM: 1
=============
```

Table 51: Case 3: Top 2 configurations of V1.1 and V3.1 after optimization search as (V3.2, V3.3)

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.12057
Number of packages: 2

_________________________
Individual score: 0.71557
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]   1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]   1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]   1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]   1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]   2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]   2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]   1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]   3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]   3$3    2$6


======================


=============
ASM: 1
=============
```

```
============================
Individual ID: 1&1&1&2&2&3&3
compute time: 0.10169
Number of packages: 3

_________________________
Individual score: 0.71243
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]   1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]   1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]   1$2    2$3
  4    4   2$2-2$1        [1 1]      [2 1]   2$2    2$1
  5    5   1$6-1$7        [3 3]      [6 7]   1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$4-2$2        [2 1]      [4 2]   1$4    2$2
  2    2   2$1-1$5        [1 2]      [1 5]   2$1    1$5
  3    3   1$4-2$3        [2 1]      [4 3]   1$4    2$3
  4    4   3$3-1$6        [1 3]      [3 6]   3$3    1$6
  5    5   3$3-2$6        [1 3]      [3 6]   3$3    2$6


======================


=============
ASM: 0.75
=============
```

Table 52 shows ASM program output for deleting an inter-package call from V1.1 as V4.1

Table 52: Case 4: ASM deleting an inter-package call from V1.1 as V4.1

• Deleted inter-PC • • ASM(V1.1, 4.1)	========== Individual ID: 1&1&1&1&1&2&2 compute time: 0.12324 Number of packages: 2 _____ Individual score: 0.71229 Individual score type: Ebad ========== intrapc # id pcid packageids classids fun1 fun2 1 1 1$1-1$2 [1 1] [1 2] 1$1 1$2 2 2 1$2-1$3 [1 1] [2 3] 1$2 1$3 3 3 1$2-2$3 [1 1] [2 3] 1$2 2$3 4 4 1$4-2$2 [1 1] [4 2] 1$4 2$2 5 5 2$2-2$1 [1 1] [2 1] 2$2 2$1 6 6 2$1-1$5 [1 1] [1 5] 2$1 1$5 7 7 1$6-1$7 [2 2] [6 7] 1$6 1$7 interpc # id pcid packageids classids fun1 fun2 1 1 3$3-1$6 [1 2] [3 6] 3$3 1$6 ========== ========== ASM: 1 ==========

Table 53shows ExASM program output for deleting an inter-package call from V1.1 as V4.1

Table 53: Case 4: ExASM deleting an inter-package call from V1.1 as V4.1

• Deleted inter-PC • ExASM(V1.1, V4.1, 0.4)	========== Individual ID: 1&1&1&1&1&2&2 compute time: 0.048132 Number of packages: 2 _____ Individual score: 0.71229 Individual score type: Ebad ========== intrapc # id pcid packageids classids fun1 fun2 1 1 1$1-1$2 [1 1] [1 2] 1$1 1$2 2 2 1$2-1$3 [1 1] [2 3] 1$2 1$3 3 3 1$2-2$3 [1 1] [2 3] 1$2 2$3 4 4 1$4-2$2 [1 1] [4 2] 1$4 2$2 5 5 2$2-2$1 [1 1] [2 1] 2$2 2$1 6 6 2$1-1$5 [1 1] [1 5] 2$1 1$5 7 7 1$6-1$7 [2 2] [6 7] 1$6 1$7 interpc # id pcid packageids classids fun1 fun2 1 1 3$3-1$6 [1 2] [3 6] 3$3 1$6 ========== ========== ExASM(w = 0.4): 0.8 ==========

Table 54 and Table 55 shows Case 4: Top 2 configurations of V1.1 and V4.1 after optimization search as (V1.2, V1.3) and (V4.2, V4.3). Note V1.2 = V1.1 since V1.1 is the top most configuration [1 1 1 1 1 2 2] ([ABCDE, FG]). V1.3 is [1 1 2 1 1 2 2] ([ABDE, CFG]). V4.2 is [1 1 1 1 1 2 2] ([ABCDE, FG]) with Ebad score 0.71229. [2 2 3 4 4 3 3]. V4.3 is [1 1 2 3 3 2 2] ([ABDE, CFG]) with Ebad score 0.69711.

Table 54: Case 4: Top 2 configurations of V1.1 and V4.1 after optimization search as (V1.2, V1.3)

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.12057
Number of packages: 2

_________________________
Individual score: 0.71557
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 1
=============
```

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.14197
Number of packages: 2

_________________________
Individual score: 0.71229
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6


======================


=============
ASM: 1
=============
```

Table 55: Case 4: Top 2 configurations of V1.1 and V4.1 after optimization search as (V4.2, V4.3)

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.12057
Number of packages: 2

_____________________________
Individual score: 0.71557
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 1
=============
```

```
============================
Individual ID: 1&1&2&3&3&2&2
compute time: 0.090684
Number of packages: 3

_____________________________
Individual score: 0.69711
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  3    3   3$3-1$6        [2 2]      [3 6]    3$3    1$6
  4    4   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$2-1$3        [1 2]      [2 3]    1$2    1$3
  2    2   1$2-2$3        [1 2]      [2 3]    1$2    2$3
  3    3   1$4-2$2        [3 1]      [4 2]    1$4    2$2
  4    4   2$1-1$5        [1 3]      [1 5]    2$1    1$5


======================


=============
ASM: 1
=============
```

Table 56 shows ASM program output for deleting an intra-package call from V1.1 to make V5.1

Table 56: Case 5: ASM deleting an intra-package call from V1.1 to make V5.1

- Deleted intra-PC
- ASM(V1.1, 5.1)

```
==============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.11955
Number of packages: 2

_____________________________
Individual score: 0.66557
Individual score type: Ebad
==============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 1
=============
```

Table 57 shows ExASM program output for deleting an intra-package call from V1.1 to make V5.1

Table 57: Case 5: ExASM deleting an intra-package call from V1.1 to make V5.1

- Deleted intra-PC
- ExASM(V1.1, V5.1, 0.4)

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.057051
Number of packages: 2

____________________________
Individual score: 0.66557
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=================
ExASM(w = 0.4): 0.91429
=================
```

Table 58 and Table 59 shows Case 5: Top 2 configurations of V1.1 and V5.1 after optimization search as (V1.2, V1.3) and (V5.2, V5.3). Note V1.2 = V1.1 since V1.1 is the top most configuration [1 1 1 1 1 2 2] ([ABCDE, FG]). V1.3 is [1 1 2 1 1 2 2] ([ABDE, CFG]). V5.2 is [1 1 1 1 1 2 2] ([ABCDE, FG]) with Ebad score 0.66557. V5.3 is supposed to be [1 1 1 1 1 1 1] ([ABCDEFG]) with Ebad score 0.6587. But this is not a desired configuration. V5.3 is [1 1 2 1 2 2 2] ([ABDE, CFG]) with Ebad score 0.62344

Table 58: Case 5: Top 2 configurations of V1.1 and V5.1 after optimization search as (V1.2, V1.3)

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.12057
Number of packages: 2

_____________________________
Individual score: 0.71557
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 1
=============
```

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.12615
Number of packages: 2

_____________________________
Individual score: 0.66557
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 1
=============
```

Table 59: Case 5: Top 2 configurations of V1.1 and V5.1 after optimization search as (V5.2, V5.3)

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.12057
Number of packages: 2

_________________________
Individual score: 0.71557
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 1
=============
```

```
============================
Individual ID: 1&1&2&1&2&2&2
compute time: 0.11711
Number of packages: 2

_________________________
Individual score: 0.62344
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  3    3   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  4    4   3$3-1$6        [2 2]      [3 6]    3$3    1$6
  5    5   1$6-1$7        [2 2]      [6 7]    1$6    1$7
  6    6   3$3-2$6        [2 2]      [3 6]    3$3    2$6


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$2-1$3        [1 2]      [2 3]    1$2    1$3
  2    2   1$2-2$3        [1 2]      [2 3]    1$2    2$3


======================


=============
ASM: 1
=============
```

Table 60 shows ASM program output for adding a class making inter-package call into V1.1 to makeV6.1

Table 60: Case 6: ASM adding a class making inter-package call into V1.1 to makeV6.1

- Added inter-PC
- ASM(V1.1, V6.1)

```
============================
Individual ID: 1&1&1&1&1&2&2&2
compute time: 0.12098
Number of packages: 2

_____________________________
Individual score: 0.73938
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$8-3$3        [2 1]      [8 3]    1$8    3$3
  2    2   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  3    3   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 0.75
=============
```

Table 61 shows ExASM program output for adding a class making inter-package call into V1.1 to makeV6.1

Table 61: Case 6: ExASM adding a class making inter-package call into V1.1 to makeV6.1

- Added inter-PC
- ExASM(V1.1, V6.1, 0.4)

```
==============================
Individual ID: 1&1&1&1&1&2&2&2
compute time: 0.053986
Number of packages: 2

_____________________________
Individual score: 0.73938
Individual score type: Ebad
==============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$8-3$3        [2 1]      [8 3]    1$8    3$3
  2    2   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  3    3   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=================
ExASM(w = 0.4): 0.86667
=================
```

Table 62 and Table 63 shows Case 6: Top 2 configurations of V1.1 and V6.1 after optimization search as (V1.2, V1.3) and (V6.2, V6.3). Note V1.2 = V1.1 since V1.1 is the top most configuration [1 1 1 1 1 2 2] ([ABCDE, FG]). V1.3 is [1 1 2 1 1 2 2] ([ABDE, CFG]). V6.2 is [1 1 1 1 1 2 2 2] ([ABCDE, FGH]) with Ebad score 0.73938. V6.3 is [1 1 2 3 3 2 2 2] ([AB, CFGH, DE]) with Ebad score 0.71447

Table 62: Case 6: Top 2 configurations of V1.1 and V6.1 after optimization search as (V1.2, V1.3)

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.12057
Number of packages: 2

_____________________________
Individual score: 0.71557
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 1
=============
```

```
============================
Individual ID: 1&1&1&1&1&2&2&2
compute time: 0.12993
Number of packages: 2

_____________________________
Individual score: 0.73938
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$8-3$3        [2 1]      [8 3]    1$8    3$3
  2    2   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  3    3   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 0.75
=============
```

Table 63: Case 6: Top 2 configurations of V1.1 and V6.1 after optimization search as (V6.2, V6.3)

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.12057
Number of packages: 2

____________________________
Individual score: 0.71557
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
____________________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 1
=============
```

```
============================
Individual ID: 1&1&2&3&3&2&2&2
compute time: 0.10592
Number of packages: 3

____________________________
Individual score: 0.71447
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  3    3   1$8-3$3        [2 2]      [8 3]    1$8    3$3
  4    4   3$3-1$6        [2 2]      [3 6]    3$3    1$6
  5    5   1$6-1$7        [2 2]      [6 7]    1$6    1$7
  6    6   3$3-2$6        [2 2]      [3 6]    3$3    2$6


interpc
  #   id      pcid   packageids   classids   fun1   fun2
____________________________________________________________

  1    1   1$2-1$3        [1 2]      [2 3]    1$2    1$3
  2    2   1$2-2$3        [1 2]      [2 3]    1$2    2$3
  3    3   1$4-2$2        [3 1]      [4 2]    1$4    2$2
  4    4   2$1-1$5        [1 3]      [1 5]    2$1    1$5


======================


=============
ASM: 1
=============
```

Table 64 shows ASM program output for dding a class making intra-package call into V1.1 to make V7.1

Table 64: Case 7: ASM adding a class making intra-package call into V1.1 to make V7.1

- Added intra-PC
- ASM(V1.1, V7.1)

```
==============================
Individual ID: 1&1&1&1&1&2&2&1
compute time: 0.12007
Number of packages: 2

_____________________________
Individual score: 0.66937
Individual score type: Ebad
==============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$8-3$3        [1 1]      [8 3]    1$8    3$3
  8    8   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 1
=============
```

Table 65 shows ExASM program output for adding a class making intra-package call into V1.1 to make V7.1

Table 65: Case 7: ExASM adding a class making intra-package call into V1.1 to make V7.1

- Added intra-PC
- ExASM(V1.1, V7.1, 0.4)

```
============================
Individual ID: 1&1&1&1&1&2&2&1
compute time: 0.055156
Number of packages: 2

____________________________
Individual score: 0.66937
Individual score type: Ebad
============================
intrapc
  #   id      pcid    packageids    classids    fun1    fun2
 ____________________________________________________________

  1    1   1$1-1$2        [1 1]       [1 2]    1$1     1$2
  2    2   1$2-1$3        [1 1]       [2 3]    1$2     1$3
  3    3   1$2-2$3        [1 1]       [2 3]    1$2     2$3
  4    4   1$4-2$2        [1 1]       [4 2]    1$4     2$2
  5    5   2$2-2$1        [1 1]       [2 1]    2$2     2$1
  6    6   2$1-1$5        [1 1]       [1 5]    2$1     1$5
  7    7   1$8-3$3        [1 1]       [8 3]    1$8     3$3
  8    8   1$6-1$7        [2 2]       [6 7]    1$6     1$7


interpc
  #   id      pcid    packageids    classids    fun1    fun2
 ____________________________________________________________

  1    1   3$3-1$6        [1 2]       [3 6]    3$3     1$6
  2    2   3$3-2$6        [1 2]       [3 6]    3$3     2$6


======================


=================
ExASM(w = 0.4): 0.925
=================
```

Table 66 and Table 67 shows Case 7: Top 2 configurations of V1.1 and V7.1 after optimization search as (V1.2, V1.3) and (V7.2, V7.3). Note V1.2 = V1.1 since V1.1 is the top most configuration [1 1 1 1 1 2 2] ([ABCDE, FG]). V1.3 is [1 1 2 1 1 2 2] ([ABDE, CFG]). V7.2 is [1 1 1 1 1 2 2 2] ([ABCDE, FGH]) with Ebad score 0.73938. V7.3 is [1 1 2 3 3 2 2 2] ([AB, CFGH, DE]) with Ebad score 0.71447. Same with V6.2 and V6.3

Table 66: Case 7: Top 2 configurations of V1.1 and V7.1 after optimization search as (V1.2, V1.3)

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.12057
Number of packages: 2

_____________________________
Individual score: 0.71557
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]   1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]   1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]   1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]   1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]   2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]   2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]   1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]   3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]   3$3    2$6


======================


=============
ASM: 1
=============
```

```
============================
Individual ID: 1&1&1&1&1&2&2&2
compute time: 0.12993
Number of packages: 2

_____________________________
Individual score: 0.73938
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]   1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]   1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]   1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]   1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]   2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]   2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]   1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$8-3$3        [2 1]      [8 3]   1$8    3$3
  2    2   3$3-1$6        [1 2]      [3 6]   3$3    1$6
  3    3   3$3-2$6        [1 2]      [3 6]   3$3    2$6


======================


=============
ASM: 0.75
=============
```

Table 67: Case 7: Top 2 configurations of V1.1 and V7.1 after optimization search as (V7.2, V7.3)

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.12057
Number of packages: 2

_____________________________
Individual score: 0.71557
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]   1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]   1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]   1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]   1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]   2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]   2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]   1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]   3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]   3$3    2$6


======================


=============
ASM: 1
=============
```

```
============================
Individual ID: 1&1&2&3&3&2&2&2
compute time: 0.10592
Number of packages: 3

_____________________________
Individual score: 0.71447
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]   1$1    1$2
  2    2   2$2-2$1        [1 1]      [2 1]   2$2    2$1
  3    3   1$8-3$3        [2 2]      [8 3]   1$8    3$3
  4    4   3$3-1$6        [2 2]      [3 6]   3$3    1$6
  5    5   1$6-1$7        [2 2]      [6 7]   1$6    1$7
  6    6   3$3-2$6        [2 2]      [3 6]   3$3    2$6


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$2-1$3        [1 2]      [2 3]   1$2    1$3
  2    2   1$2-2$3        [1 2]      [2 3]   1$2    2$3
  3    3   1$4-2$2        [3 1]      [4 2]   1$4    2$2
  4    4   2$1-1$5        [1 3]      [1 5]   2$1    1$5


======================


=============
ASM: 1
=============
```

Table 68 shows ASM program output for deleting a class making inter-package call from V1.1 to makeV8.1

Table 68: Case 8: ASM deleting a class making inter-package call from V1.1 to makeV8.1

• Deleting inter-PC
 	
• ASM(V1.1, V8.1)
	============================
	Individual ID: 1&1&1&1&2&2
	compute time: 0.086224
	Number of packages: 2
	
	Individual score: 0.91979
	Individual score type: Ebad
	============================
	intrapc
	  # id pcid packageids classids fun1 fun2
	  1 1 1$1-1$2 [1 1] [1 2] 1$1 1$2
	  2 2 1$4-2$2 [1 1] [4 2] 1$4 2$2
	  3 3 2$2-2$1 [1 1] [2 1] 2$2 2$1
	  4 4 2$1-1$5 [1 1] [1 5] 2$1 1$5
	  5 5 1$6-1$7 [2 2] [6 7] 1$6 1$7
	
	interpc
	  # id pcid packageids classids fun1 fun2
	  1 [] [] [] [] [] []
	
	======================
	
	=============
	ASM: 0.28571
	=============

Table 69 shows ExASM program output for deleting a class making inter-package call from V1.1 to makeV8.1

Table 69: Case 8: ExASM deleting a class making inter-package call from V1.1 to makeV8.1

• Deleting inter-PC • ExASM (V1.1, V8.1, 0.4)	========== Individual ID: 1&1&1&1&2&2 compute time: 0.044607 Number of packages: 2 _____ Individual score: 0.91979 Individual score type: Ebad ========== intrapc # id pcid packageids classids fun1 fun2 1 1 1$1-1$2 [1 1] [1 2] 1$1 1$2 2 2 1$4-2$2 [1 1] [4 2] 1$4 2$2 3 3 2$2-2$1 [1 1] [2 1] 2$2 2$1 4 4 2$1-1$5 [1 1] [1 5] 2$1 1$5 5 5 1$6-1$7 [2 2] [6 7] 1$6 1$7 interpc # id pcid packageids classids fun1 fun2 1 [] [] [] [] [] [] ========== ========== ExASM(w = 0.4): 0.42857 ==========

Table 70 and Table 71 shows Case 8: Top 2 configurations of V1.1 and V6.1 after optimization search as (V1.2, V1.3) and (V8.2, V8.3). Note V1.2 = V1.1 since V1.1 is the top most configuration [1 1 1 1 1 2 2] ([ABCDE,FG]). V1.3 is [1 1 2 1 1 2 2] ([ABDE,CFG]). V8.2 is [1 1 1 1 2 2] ([ABDE, FG]) with Ebad score 0.91979. V8.3 is [1 1 2 2 3 3] ([AB, CD, EF]) with Ebad score 0.84676.

Table 70: Case 8: Top 2 configurations of V1.1 and V6.1 after optimization search as (V1.2, V1.3)

```
============================
Individual ID: 1&1&1&1&2&2
compute time: 0.12057
Number of packages: 2

_________________________
Individual score: 0.71557
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 1
=============
```

```
============================
Individual ID: 1&1&1&1&2&2
compute time: 0.074213
Number of packages: 2

_________________________
Individual score: 0.91979
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  3    3   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  4    4   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  5    5   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id   pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1   []     []           []         []     []     []


======================


=============
ASM: 0.28571
=============
```

Table 71: Case 8: Top 2 configurations of V1.1 and V6.1 after optimization search as (V8.2, V8.3)

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.12057
Number of packages: 2

_________________________
Individual score: 0.71557
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 1
=============
```

```
============================
Individual ID: 1&1&2&2&3&3
compute time: 0.071053
Number of packages: 3

_________________________
Individual score: 0.84676
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  3    3   1$6-1$7        [3 3]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________

  1    1   1$4-2$2        [2 1]      [4 2]    1$4    2$2
  2    2   2$1-1$5        [1 2]      [1 5]    2$1    1$5


======================


=============
ASM: 0.75
=============
```

Table 72 shows ASM program output for deleting a class making intra-package call from V1.1 to makeV9.1

Table 72: Case 9: ASM deleting a class making intra-package call from V1.1 to makeV9.1

- Deleting a class
- ASM(V1.1, 9.1)

```
==============================
Individual ID: 1&1&1&1&1&2
compute time: 0.12562
Number of packages: 2

------------------------------
Individual score: 0.46542
Individual score type: Ebad
==============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
-------------------------------------------------------
  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5


interpc
  #   id      pcid   packageids   classids   fun1   fun2
-------------------------------------------------------
  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 1
=============
```

Table 73 shows ExASM program output for deleting a class making intra-package call from V1.1 to makeV9.1

Table 73: Case 9: ExASM deleting a class making intra-package call from V1.1 to makeV9.1

• Deleting a class
 	
• ExASM(V1.1, V9.1, 0.4)
	==========
	Individual ID: 1&1&1&1&1&2
	compute time: 0.10429
	Number of packages: 2
	
	Individual score: 0.46542
	Individual score type: Ebad
	==========
	intrapc
	`#  id  pcid  packageids  classids  fun1  fun2`
	`1  1  1$1-1$2  [1 1]  [1 2]  1$1  1$2`
	`2  2  1$2-1$3  [1 1]  [2 3]  1$2  1$3`
	`3  3  1$2-2$3  [1 1]  [2 3]  1$2  2$3`
	`4  4  1$4-2$2  [1 1]  [4 2]  1$4  2$2`
	`5  5  2$2-2$1  [1 1]  [2 1]  2$2  2$1`
	`6  6  2$1-1$5  [1 1]  [1 5]  2$1  1$5`
	
	interpc
	`#  id  pcid  packageids  classids  fun1  fun2`
	`1  1  3$3-1$6  [1 2]  [3 6]  3$3  1$6`
	`2  2  3$3-2$6  [1 2]  [3 6]  3$3  2$6`
	
	==========
	
	==========
	ExASM(w = 0.4): 0.91429
	==========

Table 74 and Table 75 shows Case 9: Top 2 configurations of V1.1 and V9.1 after optimization search as (V1.2, V1.3) and (V9.2, V9.3). Note V1.2 = V1.1 since V1.1 is the top most configuration [1 1 1 1 1 2 2] ([ABCDE, FG]). V1.3 is [1 1 2 1 1 2 2] ([ABDE, CFG]). V9.2 is supposed to be [1 1 1 1 1 1 1] ([ABCDEFG]) with Ebad score 0.72139. But this is not a desired configuration. V9.2 is [1 1 2 3 3 2] ([AB, CF, DE]) with Ebad score 0.67488. V6.3 is [1 1 1 2 2 1] ([ABCF, DE]) with Ebad score 0.66748

Table 74: Case 9: Top 2 configurations of V1.1 and V9.1 after optimization search as (V1.2, V1.3)

```
============================
Individual ID: 1&1&1&1&1&2&2
compute time: 0.12057
Number of packages: 2

_________________________
Individual score: 0.71557
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 1
=============
```

```
============================
Individual ID: 1&1&2&3&3&2
compute time: 0.10349
Number of packages: 3

_________________________
Individual score: 0.67488
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  3    3   3$3-1$6        [2 2]      [3 6]    3$3    1$6
  4    4   3$3-2$6        [2 2]      [3 6]    3$3    2$6


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$2-1$3        [1 2]      [2 3]    1$2    1$3
  2    2   1$2-2$3        [1 2]      [2 3]    1$2    2$3
  3    3   1$4-2$2        [3 1]      [4 2]    1$4    2$2
  4    4   2$1-1$5        [1 3]      [1 5]    2$1    1$5


======================


=============
ASM: 0.75
=============
```

Table 75: Case 9: Top 2 configurations of V1.1 and V9.1 after optimization search as (V9.2, V9.3)

```
============================
Individual ID: 1&1&1&1&2&2
compute time: 0.12057
Number of packages: 2

_____________________
Individual score: 0.71557
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   1$4-2$2        [1 1]      [4 2]    1$4    2$2
  5    5   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  6    6   2$1-1$5        [1 1]      [1 5]    2$1    1$5
  7    7   1$6-1$7        [2 2]      [6 7]    1$6    1$7


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   3$3-1$6        [1 2]      [3 6]    3$3    1$6
  2    2   3$3-2$6        [1 2]      [3 6]    3$3    2$6


======================


=============
ASM: 1
=============
```

```
============================
Individual ID: 1&1&1&2&2&1
compute time: 0.097013
Number of packages: 2

_____________________
Individual score: 0.66748
Individual score type: Ebad
============================
intrapc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$1-1$2        [1 1]      [1 2]    1$1    1$2
  2    2   1$2-1$3        [1 1]      [2 3]    1$2    1$3
  3    3   1$2-2$3        [1 1]      [2 3]    1$2    2$3
  4    4   2$2-2$1        [1 1]      [2 1]    2$2    2$1
  5    5   3$3-1$6        [1 1]      [3 6]    3$3    1$6
  6    6   3$3-2$6        [1 1]      [3 6]    3$3    2$6


interpc
  #   id      pcid   packageids   classids   fun1   fun2
_____________________________________________________________

  1    1   1$4-2$2        [2 1]      [4 2]    1$4    2$2
  2    2   2$1-1$5        [1 2]      [1 5]    2$1    1$5


======================


=============
ASM: 0.75
=============
```

Appendix 2: GA and DE Results

Table 76 shows the result of GA experiment. The columns **mutation**, **crossover** and **creation** take their values from the different settings according to Table 26. The average is the average of running same combination of parameter values 5 times. **Best configuration of 5 trial runs** in the best configuration among all the 5 combinations.

Table 26: GA parameters setting

	GA parameters			
mutation	1	2	3	4
	Mutate Adaptive feasible	Mymutate = 0.2	Mymutate = 0.5	Mymutate = 0.8
crossover	1	2	3	4
	crxscatter	crxrlfipr	Crxrandperm: noperm = noclass	Crxrandperm: noperm = 2*noclass
creation	1	2	3	
	Create: mean = 0.2 Create: sdv = 0.07	Create: mean = 0.2 Create: sdv = 0.1	Create: mean = 0.2 Create: sdv = 0.3	
	4	5	6	
	Create: mean = 0.5 Create: sdv = 0.07	Create: mean = 0.5 Create: sdv = 0.1	Create: mean = 0.5 Create: sdv = 0.3	
	7	8	9	
	Create: mean = 0.7 Create: sdv = 0.07	Create: mean = 0.7 Create: sdv = 0.1	Create: mean = 0.7 Create: sdv = 0.3	

Table 76: GA experiment result

mutation	crossover	creation	average	best configuration of 5 trial runs						
1	1	1	-0.7016	7	7	1	7	7	1	1
1	1	2	-0.4618	7	7	7	1	1	7	1
1	1	3	-0.5378	1	5	1	5	1	3	3
1	1	4	-0.6907	1	1	1	7	7	6	6
1	1	5	-0.7013	1	1	4	6	6	4	4
1	1	6	-0.4693	6	6	7	5	5	1	7
1	1	7	-0.7016	1	1	7	1	1	7	7
1	1	8	-0.7016	7	7	1	7	7	1	1

1	1	9	-0.7016	1	1	7	1	1	7	7
1	2	1	-0.6226	7	7	1	1	1	2	2
1	2	2	-0.7016	7	7	1	7	7	1	1
1	2	3	-0.7099	1	1	1	1	1	1	1
1	2	4	-0.5413	7	5	5	5	7	4	4
1	2	5	-0.5378	1	5	1	5	1	3	3
1	2	6	-0.4669	6	3	6	2	2	3	3
1	2	7	-0.5705	7	1	7	1	1	2	2
1	2	8	-0.7013	3	3	2	5	5	2	2
1	2	9	-0.6907	3	3	3	4	4	6	6
1	3	1	-0.4693	6	6	7	5	5	1	7
1	3	2	-0.7016	3	3	1	3	3	1	1
1	3	3	-0.7016	7	7	1	7	7	1	1
1	3	4	-0.7137	1	1	1	1	1	2	2
1	3	5	-0.7013	3	3	2	5	5	2	2
1	3	6	-0.4693	6	6	7	5	5	1	7
1	3	7	-0.7016	7	7	1	7	7	1	1
1	3	8	-0.7016	1	1	7	1	1	7	7
1	3	9	-0.6226	7	7	1	1	1	2	2
1	4	1	-0.7016	7	7	1	7	7	1	1
1	4	2	-0.5413	7	5	5	5	7	4	4
1	4	3	-0.7016	5	5	3	5	5	3	3
1	4	4	-0.4669	6	3	6	2	2	3	3
1	4	5	-0.7016	1	1	7	1	1	7	7
1	4	6	-0.7013	3	3	2	5	5	2	2
1	4	7	-0.6907	3	3	3	4	4	6	6
1	4	8	-0.4693	6	6	7	5	5	1	7
1	4	9	-0.7016	3	3	1	3	3	1	1
1	5	1	-0.4618	7	7	7	1	1	7	1
1	5	2	-0.5413	7	5	5	5	7	4	4
1	5	3	-0.7016	5	5	3	5	5	3	3
1	5	4	-0.4669	6	3	6	2	2	3	3
1	5	5	-0.5705	7	1	7	1	1	2	2
1	5	6	-0.4669	6	3	6	2	2	3	3
1	5	7	-0.6907	3	3	3	4	4	6	6
1	5	8	-0.4693	6	6	7	5	5	1	7
1	5	9	-0.7016	3	3	1	3	3	1	1
2	1	1	-0.7016	7	7	1	7	7	1	1
2	1	2	-0.7137	1	1	1	1	1	2	2
2	1	3	-0.5705	7	1	7	1	1	6	6
2	1	4	-0.7016	1	1	7	1	1	7	7
2	1	5	-0.7016	7	7	1	7	7	1	1
2	1	6	-0.7016	1	1	7	1	1	7	7

2	1	7	-0.6226	7	7	1	1	1	2	2
2	1	8	-0.7016	7	7	1	7	7	1	1
2	1	9	-0.7099	1	1	1	1	1	1	1
2	2	1	-0.7137	1	1	1	1	1	1	1
2	2	2	-0.5413	7	5	5	5	7	4	4
2	2	3	-0.7016	5	5	3	5	5	3	3
2	2	4	-0.4669	6	3	6	2	2	3	3
2	2	5	-0.5705	7	1	7	1	1	2	2
2	2	6	-0.7013	3	3	2	5	5	2	2
2	2	7	-0.6907	3	3	3	4	4	6	6
2	2	8	-0.4693	6	6	7	5	5	1	7
2	2	9	-0.7016	3	3	1	3	3	1	1
2	3	1	-0.7016	7	7	1	7	7	1	1
2	3	2	-0.7137	1	1	1	1	1	2	2
2	3	3	-0.5705	7	1	7	1	1	6	6
2	3	4	-0.7016	1	1	7	1	1	7	7
2	3	5	-0.7016	7	7	1	7	7	1	1
2	3	6	-0.7016	1	1	7	1	1	7	7
2	3	7	-0.6226	7	7	1	1	1	2	2
2	3	8	-0.7016	7	7	1	7	7	1	1
2	3	9	-0.7099	1	1	1	1	1	1	1
2	4	1	-0.7137	1	1	1	1	1	1	1
2	4	2	-0.5413	7	5	5	5	7	4	4
2	4	3	-0.7016	5	5	3	5	5	3	3
2	4	4	-0.4669	6	3	6	2	2	3	3
2	4	5	-0.5705	7	1	7	1	1	2	2
2	4	6	-0.7013	3	3	2	5	5	2	2
2	4	7	-0.6907	3	3	3	4	4	6	6
2	4	8	-0.4693	6	6	7	5	5	1	7
2	4	9	-0.7016	3	3	1	3	3	1	1
2	5	1	-0.7016	7	7	1	7	7	1	1
2	5	2	-0.7137	1	1	1	1	1	2	2
2	5	3	-0.5705	7	1	7	1	1	6	6
2	5	4	-0.7016	1	1	7	1	1	7	7
2	5	5	-0.4618	7	7	7	1	1	7	1
2	5	6	-0.7016	1	1	7	1	1	7	7
2	5	7	-0.6226	7	7	1	1	1	2	2
2	5	8	-0.7016	7	7	1	7	7	1	1
2	5	9	-0.7099	1	1	1	1	1	1	1
3	1	1	-0.5705	7	1	7	1	1	2	2
3	1	2	-0.7013	3	3	2	5	5	2	2
3	1	3	-0.6907	3	3	3	4	4	6	6
3	1	4	-0.4693	6	6	7	5	5	1	7

3	1	5	-0.7016	3	3	1	3	3	1	1
3	1	6	-0.7016	7	7	1	7	7	1	1
3	1	7	-0.7137	1	1	1	1	1	2	2
3	1	8	-0.5705	7	1	7	1	1	6	6
3	1	9	-0.7016	1	1	7	1	1	7	7
3	2	1	-0.4693	6	6	7	5	5	1	7
3	2	2	-0.7016	3	3	1	3	3	1	1
3	2	3	-0.7016	7	7	1	7	7	1	1
3	2	4	-0.7016	7	7	1	7	7	1	1
3	2	5	-0.4693	6	6	7	5	5	1	7
3	2	6	-0.7016	3	3	1	3	3	1	1
3	2	7	-0.7016	1	1	7	1	1	7	7
3	2	8	-0.6226	7	7	1	1	1	2	2
3	2	9	-0.7016	7	7	1	7	7	1	1
3	3	1	-0.7137	1	1	1	1	1	1	1
3	3	2	-0.7137	1	1	1	1	1	1	1
3	3	3	-0.7016	7	7	1	7	7	1	1
3	3	4	-0.7156	1	1	1	1	1	2	2
3	3	5	-0.5705	7	1	7	1	1	2	2
3	3	6	-0.7013	3	3	2	5	5	2	2
3	3	7	-0.6907	3	3	3	4	4	6	6
3	3	8	-0.4693	6	6	7	5	5	1	7
3	3	9	-0.7016	3	3	1	3	3	1	1
3	4	1	-0.7016	7	7	1	7	7	1	1
3	4	2	-0.7137	1	1	1	1	1	2	2
3	4	3	-0.5705	7	1	7	1	1	6	6
3	4	4	-0.7016	1	1	7	1	1	7	7
3	4	5	-0.7156	7	7	7	7	7	1	1
3	4	6	-0.6907	3	3	3	4	4	6	6
3	4	7	-0.4693	6	6	7	5	5	1	7
3	4	8	-0.7016	3	3	1	3	3	1	1
3	4	9	-0.7016	7	7	1	7	7	1	1
3	5	1	-0.7137	1	1	1	1	1	1	1
3	5	2	-0.7137	1	1	1	1	1	1	1
3	5	3	-0.7137	1	1	1	1	1	1	1
3	5	4	-0.7137	1	1	1	1	1	1	1
3	5	5	-0.7137	1	1	1	1	1	1	1
3	5	6	-0.7137	1	1	1	1	1	2	2
3	5	7	-0.7137	1	1	1	1	1	1	1
3	5	8	-0.7137	1	1	1	1	1	1	1
3	5	9	-0.7137	1	1	1	1	1	2	2
4	1	1	-0.5705	7	1	7	1	1	2	2
4	1	2	-0.5705	7	1	7	1	1	2	2

4	1	3	-0.7013	3	3	2	5	5	2	2
4	1	4	-0.6907	3	3	3	4	4	6	6
4	1	5	-0.4693	6	6	7	5	5	1	7
4	1	6	-0.7016	3	3	1	3	3	1	1
4	1	7	-0.7016	7	7	1	7	7	1	1
4	1	8	-0.6907	3	3	3	4	4	6	6
4	1	9	-0.5705	7	1	7	1	1	6	6
4	2	1	-0.7016	1	1	7	1	1	7	7
4	2	2	-0.7016	7	7	1	7	7	1	1
4	2	3	-0.7013	3	3	2	5	5	2	2
4	2	4	-0.6907	3	3	3	4	4	6	6
4	2	5	-0.4693	6	6	7	5	5	1	7
4	2	6	-0.7016	3	3	1	3	3	1	1
4	2	7	-0.7016	7	7	1	7	7	1	1
4	2	8	-0.4693	6	6	7	5	5	1	7
4	2	9	-0.5705	7	1	7	1	1	6	6
4	3	1	-0.7016	1	1	7	1	1	7	7
4	3	2	-0.7016	7	7	1	7	7	1	1
4	3	3	-0.6226	7	7	1	1	1	2	2
4	3	4	-0.7016	7	7	1	7	7	1	1
4	3	5	-0.7016	1	1	7	1	1	7	7
4	3	6	-0.7016	7	7	1	7	7	1	1
4	3	7	-0.7016	1	1	7	1	1	7	7
4	3	8	-0.6226	7	7	1	1	1	2	2
4	3	9	-0.7016	5	5	3	5	5	3	3
4	4	1	-0.4669	6	3	6	2	2	3	3
4	4	2	-0.5705	7	1	7	1	1	2	2
4	4	3	-0.7013	3	3	2	5	5	2	2
4	4	4	-0.6907	3	3	3	4	4	6	6
4	4	5	-0.4693	6	6	7	5	5	1	7
4	4	6	-0.7016	3	3	1	3	3	1	1
4	4	7	-0.7016	7	7	1	7	7	1	1
4	4	8	-0.7016	7	7	1	7	7	1	1
4	4	9	-0.5705	7	1	7	1	1	6	6
4	5	1	-0.7016	1	1	7	1	1	7	7
4	5	2	-0.7016	7	7	1	7	7	1	1
4	5	3	-0.7016	1	1	7	1	1	7	7
4	5	4	-0.6226	7	7	1	1	1	2	2
4	5	5	-0.7016	7	7	1	7	7	1	1
4	5	6	-0.7099	1	1	1	1	1	1	1
4	5	7	-0.7137	1	1	1	1	1	1	1
4	5	8	-0.7137	1	1	1	1	1	1	1
4	5	9	-0.7137	1	1	1	1	1	2	2

Table 77 shows the result of DE experiment. The columns **mutation**, **crossover** and **creation** take their values from the different settings according to Table 28. The average is the average of running same combination of parameter values 5 times. **Best configuration of 5 trial runs** in the best configuration among all the 5 combinations.

Table 28: DE parameters

	DE parameters		
Mutation scale	1	2	3
	0.2	0.5	0.8
Crossover rate	1	2	3
	0.5	0.7	0.9
creation	1	2	3
	Create: mean = 0.2 Create: sdv = 0.07	Create: mean = 0.2 Create: sdv = 0.1	Create: mean = 0.2 Create: sdv = 0.3
	4	5	6
	Create: mean = 0.5 Create: sdv = 0.07	Create: mean = 0.5 Create: sdv = 0.1	Create: mean = 0.5 Create: sdv = 0.3
	7	8	9
	Create: mean = 0.7 Create: sdv = 0.07	Create: mean = 0.7 Create: sdv = 0.1	Create: mean = 0.7 Create: sdv = 0.3

Table 77: DE experiment results

mutation	crossover	creation	average	best configuration of 5 trial runs						
1	1	1	-0.7013	3	3	2	5	5	2	2
1	1	2	-0.7016	5	5	3	5	5	3	3
1	1	3	-0.7013	1	1	4	6	6	4	4
1	1	4	-0.6907	3	3	3	4	4	6	6
1	1	5	-0.4693	6	6	7	5	5	1	7
1	1	6	-0.7137	1	1	1	1	1	1	1
1	1	7	-0.5705	7	1	7	1	1	2	2
1	1	8	-0.5705	7	1	7	1	1	6	6

1	1	9	-0.4693	6	6	7	5	5	1	7
1	2	1	-0.6907	3	3	3	4	4	6	6
1	2	2	-0.7016	1	1	7	1	1	7	7
1	2	3	-0.7013	3	3	2	5	5	2	2
1	2	4	-0.4669	6	3	6	2	2	3	3
1	2	5	-0.6907	3	3	3	4	4	6	6
1	2	6	-0.7156	1	1	1	1	1	2	2
1	2	7	-0.5705	7	1	7	1	1	2	2
1	2	8	-0.7016	7	7	1	7	7	1	1
1	2	9	-0.7016	3	3	1	3	3	1	1
1	3	1	-0.5705	7	1	7	1	1	6	6
1	3	2	-0.7016	7	7	1	7	7	1	1
1	3	3	-0.7016	1	1	7	1	1	7	7
1	3	4	-0.4669	6	3	6	2	2	3	3
1	3	5	-0.7016	1	1	7	1	1	7	7
1	3	6	-0.4618	7	7	7	1	1	7	1
1	3	7	-0.7013	3	3	2	5	5	2	2
1	3	8	-0.7016	7	7	1	7	7	1	1
1	3	9	-0.7016	7	7	1	7	7	1	1
2	1	1	-0.4693	6	6	7	5	5	1	7
2	1	2	-0.7137	1	1	1	1	1	2	2
2	1	3	-0.4693	6	6	7	5	5	1	7
2	1	4	-0.7156	1	1	1	1	1	7	7
2	1	5	-0.7156	3	3	3	3	3	2	2
2	1	6	-0.7016	3	3	1	3	3	1	1
2	1	7	-0.7016	7	7	1	7	7	1	1
2	1	8	-0.7016	3	3	1	3	3	1	1
2	1	9	-0.7099	1	1	1	1	1	1	1
2	2	1	-0.7016	7	7	1	7	7	1	1
2	2	2	-0.4693	6	6	7	5	5	1	7
2	2	3	-0.7016	7	7	1	7	7	1	1
2	2	4	-0.7156	7	7	7	7	7	2	2
2	2	5	-0.7156	1	1	1	1	1	2	2
2	2	6	-0.5378	1	5	1	5	1	3	3
2	2	7	-0.4693	6	6	7	5	5	1	7
2	2	8	-0.5413	7	5	5	5	7	4	4
2	2	9	-0.7137	1	1	1	1	1	2	2
2	3	1	-0.7137	1	1	1	1	1	1	1
2	3	2	-0.7016	3	3	1	3	3	1	1
2	3	3	-0.7016	7	7	1	7	7	1	1
2	3	4	-0.7156	1	1	1	1	1	2	2

2	3	5	-0.7156	6	6	6	6	6	2	2
2	3	6	-0.7016	7	7	1	7	7	1	1
2	3	7	-0.7016	7	7	1	7	7	1	1
2	3	8	-0.7016	1	1	7	1	1	7	7
2	3	9	-0.6907	1	1	1	7	7	6	6
3	1	1	-0.5705	7	1	7	1	1	2	2
3	1	2	-0.4693	6	6	7	5	5	1	7
3	1	3	-0.7016	7	7	1	7	7	1	1
3	1	4	-0.7137	1	1	1	1	1	2	2
3	1	5	-0.7016	1	1	7	1	1	7	7
3	1	6	-0.5705	7	1	7	1	1	6	6
3	1	7	-0.7016	7	7	1	7	7	1	1
3	1	8	-0.7016	7	7	1	7	7	1	1
3	1	9	-0.7013	3	3	2	5	5	2	2
3	2	1	-0.7016	1	1	7	1	1	7	7
3	2	2	-0.7016	3	3	1	3	3	1	1
3	2	3	-0.7016	1	1	7	1	1	7	7
3	2	4	-0.7016	1	1	7	1	1	7	7
3	2	5	-0.7099	1	1	1	1	1	1	1
3	2	6	-0.6226	7	7	1	1	1	2	2
3	2	7	-0.7137	1	1	1	1	1	2	2
3	2	8	-0.6226	7	7	1	1	1	2	2
3	2	9	-0.7137	1	1	1	1	1	1	1
3	3	1	-0.4693	6	6	7	5	5	1	7
3	3	2	-0.5378	1	5	1	5	1	3	3
3	3	3	-0.6226	7	7	1	1	1	2	2
3	3	4	-0.7099	1	1	1	1	1	1	1
3	3	5	-0.5413	7	5	5	5	7	4	4
3	3	6	-0.7016	3	3	1	3	3	1	1
3	3	7	-0.7016	7	7	1	7	7	1	1
3	3	8	-0.6907	3	3	3	4	4	6	6
3	3	9	-0.7013	3	3	2	5	5	2	2

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